

Asymmetric Adjustment Toward Optimal Capital Structure: Evidence From a Crisis*

Abstract

We employ dynamic threshold partial adjustment models to study the asymmetries in firms' adjustments toward their target leverage. Using a sample of US firms during 2002–2012, we document a negative impact of the Global Financial Crisis on the speed of leverage adjustment. In our subperiod analysis, we find moderate evidence of cross-sectional heterogeneity in this speed, which seems more pronounced pre-crisis and provides little support for the financial constraint view. For the pre-crisis period, more constrained firms, such as those with high growth, with large investment, of small size, and with volatile earnings, adjust their capital structures more quickly than their less constrained counterparts. These firms rely heavily on external funds to offset their large financing deficits, suggesting that their higher adjustment speeds may be driven by lower adjustment costs that are shared with the transaction costs of accessing external capital markets. For the crisis period, the speed of adjustment only varies with the deviation from target leverage, with only firms having sufficiently large deviations attempting to revert to the target, albeit slowly. Overall, our results provide new evidence of both cross-sectional and time-varying asymmetries in capital structure adjustments, which is consistent with the trade-off theory.

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1 Introduction

Since the irrelevance theorem by Modigliani and Miller (1958), three main views of corporate capital structure have been advanced in which the method of financing matters: the trade-off theory, the pecking order theory, and the market timing hypothesis. The trade-off theory, in both its static and dynamic forms, predicts an optimal capital structure that balances the costs (e.g., financial distress costs) against the benefits (e.g., debt interest tax shield) of debt financing; see, for example, Kraus and Litzenberger (1973) for a static trade-off model and Strebulaev (2007) for a dynamic model. Under this framework, corporate leverage is predicted to exhibit mean reversion as firms seek to adjust toward their target leverage. The pecking order theory, based on asymmetric information and adverse selection, suggests that a firm's observed mix of debt and equity simply reflects its cumulative financing decisions over time, whereby internal finance is preferred over external finance and debt is preferred over equity (Myers and Majluf, 1984; Myers, 1984). The market timing hypothesis posits that capital structure decisions are driven by market timing considerations in which firms attempt to time the equity markets by issuing shares when market conditions are favorable (Baker and Wurgler, 2002). Neither the pecking order theory nor the market timing hypothesis predicts the existence of target leverage ratios and firms' adjustments toward those targets. Hence, a large body of empirical research has tested the trade-off theory against these alternative views of capital structure by examining whether and how fast firms move toward target leverage; see Frank and Goyal (2007) for a comprehensive survey.

Existing studies so far have mainly used a linear, partial adjustment model of leverage to estimate the speed of adjustment (hereafter SOA), i.e., the speed with which firms adjust their capital structures toward target leverage. For example, Flannery and Rangan (2006) find that over the period 1965–2001, US firms adjust at a rate of 34% per year. Examining international data in the G-5 countries, Antoniou et al. (2008) also document reasonably fast adjustment speeds for firms in the US (32%), the UK (32%), and France (39%). Taken together, these empirical studies provide evidence of active target adjustment behavior as predicted by the trade-off framework.

Most recent research has begun to investigate two important issues in the study of the SOA, issues that have not been thoroughly investigated by the aforementioned studies. The first issue is how to obtain a consistent estimate of the SOA in short, dynamic panels with (unobserved) firm fixed effects, in which the precision of the estimate is highly sensitive to the econometric methods and procedures

used (e.g., Huang and Ritter, 2009; Flannery and Hankins, 2013).¹ The second issue, which is the focus of this paper, is whether there exists asymmetry in target adjustment behavior such that firms take different paths toward their target leverage, at potentially heterogeneous rates. One main source of the heterogeneity in the SOA is the differential adjustment costs facing firms with different characteristics or at different positions relative to their target leverage. Dynamic trade-off models, for example, suggest that firms may have a range of leverage targets and that they only adjust their capital structures when the costs of adjustment can be offset by the benefits of adjustment (i.e., the benefits of being close to or at leverage targets) (Fischer et al., 1989; Leary and Roberts, 2005). An important implication follows that the magnitude and speed of the adjustment are dependent on how far the actual leverage ratio is from the target ratio. Firms deviating from target leverage may have an incentive to undertake quick adjustment, especially when they face a fixed adjustment cost.

Another source of heterogeneity in the SOA is the time-series variation in macroeconomic conditions that affect corporate leverage and dynamic leverage adjustment. According to the credit channel theory, leverage is pro-cyclical because firms borrow less during an economic downturn, when their balance sheets and financial conditions (e.g., the value of their collateral) deteriorate (Bernake and Gertler, 1989; Kiyotaki and Moore, 1997). Moreover, Hackbarth et al. (2006) show theoretically that firms adjust their capital structures more frequently in economic expansions than in recessions. The leverage rebalancing thresholds are higher in recessions because the leverage adjustment costs tend to increase under adverse macroeconomic conditions. These arguments suggest that the stage of the business cycle should be positively related to the SOA. The recent Global Financial Crisis of 2007–2009 and the resulting economic recession provide an excellent testing ground for this relationship. Several studies show, for example, that the crisis had dramatic effects on corporate financial policies (Campello et al., 2010; Duchin et al., 2010; Campello et al., 2011). Overall, the above arguments and findings indicate that the SOA should vary over time, being lower during the crisis period.

In this paper, we address these important empirical issues regarding the estimation of SOA and asymmetries in capital structure adjustments. Our contribution is two-fold. First, we are the first to examine both the cross-sectional and time-varying heterogeneity in the SOA. Second, we employ a new approach using dynamic threshold partial adjustment models of leverage, which enables us to con-

¹It is well-established in the literature that the pooled OLS estimates of the SOA (Fama and French, 2002) are biased downward and the fixed-effects estimates (Flannery and Rangan, 2006) are biased upward, while the GMM (Ozkan, 2001) and system GMM estimates (Antoniou et al., 2008; Lemmon et al., 2008) provide the intermediate (unbiased) cases.

sistently estimate the heterogeneous adjustment speeds for firms facing differential adjustment costs, under different financing regimes and different states of the economy. To study the cross-sectional asymmetry in the SOA, we consider several firm-specific variables that may affect the adjustment costs, namely growth opportunities, investment, firm size, earnings volatility, the Size–Age index (hereafter SA, a measure of financial constraints proposed by Hadlock and Pierce (2010)), and deviations from target leverage. To examine the time-series variation in the SOA, we compare the SOA estimated for the pre-crisis period with that estimated for the crisis period. Overall, our approach is capable of testing the validity of the dynamic trade-off theory because it explicitly allows for asymmetric and costly capital structure adjustments.

Using a recent sample of US firms during 2002–2012, we provide the first evidence in the literature of the negative impact of the Global Financial Crisis on the SOA. While we document strong and robust evidence of the time-varying heterogeneity in the SOA, we observe weaker cross-sectional variation in this speed. For the whole sample period, there is limited evidence of threshold effects and asymmetric adjustment speeds conditional on the firm-specific variables proxying for financial constraints. In our subperiod analysis, however, we document stronger cross-sectional heterogeneity in the SOA, which is most pronounced in the pre-crisis years. Pre-crisis, we find that more constrained firms, including those with high growth, with large investment, of small size, with volatile earnings, and with a high SA index, move toward their target leverage more rapidly than their less constrained counterparts. These results provide little support for the financial constraint argument, suggesting that firm-specific measures of constraints play a less important role than supply-side external factors, i.e., the credit shock triggered by the crisis. Our analysis of the firm-specific characteristics reveals that constrained firms have large financing deficits, which they offset by using external funds. Thus, these firms have higher adjustment speeds possibly because of lower adjustment costs that can be shared with the transaction costs of raising external finance (Faulkender et al., 2012). For the crisis period, the SOA only varies cross-sectionally with the deviation from target leverage. Firms with large deviations attempt to revert to their target leverage, albeit at slow rates, while those with small deviations make no such attempt. Finally, comparing the pre-crisis and crisis results, we find that the negative effects of the crisis on the adjustment speeds are also asymmetric: they seem more pronounced for firms facing more financial constraints. Overall, our results provide new evidence of both time-varying and cross-sectional asymmetries in capital structure adjustments, which is broadly consistent with the trade-off theory.

Our study paper is related to, and improves on, a few recent studies that have started to examine the implications of costly adjustment on dynamic leverage rebalancing. Drobetz et al. (2006) investigate the impact of various firm-specific variables on the SOA, although unlike our paper, the authors do not explicitly account for the asymmetries in capital structure adjustments. More recently, some research has explicitly allowed for cross-sectional heterogeneity in the SOA, conditional on a number of factors, namely (i) firms' specific characteristics proxying for financial constraints (e.g., Dang et al., 2011; Elsas and Florysiak, 2011), (ii) the magnitude of firms' deviation from target leverage and/or their financing gaps (e.g., Byoun, 2008), or (iii) firms' cash flow realizations (e.g., Faulkender et al., 2012). Unlike our paper, however, these studies generally adopt a simple approach based on dummy variables or sample splitting using given thresholds (e.g., the medians), which involves a degree of arbitrariness and is likely to suffer from a sample selection bias problem (Hansen, 2000). Simply put, these existing studies may not provide accurate estimates of the heterogeneous adjustment speeds. We address this crucial drawback by employing a threshold partial adjustment model in which the threshold is estimated within the model rather than being imposed arbitrarily *ex ante*. Hence, our approach provides consistent estimates of the (heterogeneous) SOA. In addition, by categorizing firms into different financing regimes using the threshold estimates, we provide important insights into the characteristics of firms that have differential adjustment costs and consequently take asymmetric adjustment paths.

Our study contributes to the literature examining the effects of macroeconomic conditions on corporate capital structure (e.g., Korajczyk and Levy, 2003; Covas and Den Haan, 2011; Erel et al., 2012). In particular, our empirical work is related to a strand of research focusing on the effects of business cycle variables on dynamic capital structure adjustments (Drobetz and Wanzenried, 2006; Cook and Tang, 2010). We extend this research agenda by studying the impacts of the recent Global Financial Crisis and the associated credit shock on the speed of leverage adjustment. In doing so, we provide novel evidence of both cross-sectional and time-varying heterogeneity in the SOA. Our analysis also contributes to a growing literature investigating the effects of the crisis on corporate financial policies (Campello et al., 2010; Ivashina and Scharfstein, 2010; Duchin et al., 2010; Campello et al., 2011). We document new evidence that the crisis does not only influence the leverage ratio, but also the speed of leverage adjustment.

Finally, our paper is related to a recent study by Dang et al. (2012), who also employ dynamic panel threshold models to examine asymmetric capital structure adjustments. We differ from this study in a

number of important ways. First, in terms of methods, Dang et al. (2012) assume that both the SOA and the long-run relationships between target leverage and its determining factors can be heterogeneous under different financing regimes. However, we follow the conventional approach in the literature (Byoun, 2008; Faulkender et al., 2012) and assume homogeneous long-run target relationships. Hence, in line with most theoretical and empirical research in the literature, the focus of our paper is to identify and compare the (heterogeneous) speeds with which firms adjust toward a common long-run target leverage ratio (or a target range more generally), albeit under different regimes. Second, while Dang et al. (2012) document some UK evidence of heterogeneous adjustment speeds for the period 1997–2003, we provide new US evidence obtained using the dynamic threshold models for a more recent period 2002–2012. Third, and most importantly, we examine not only the cross-sectional heterogeneity in the SOA, but also the time-varying asymmetry in this speed, especially the asymmetry caused by the Global Financial Crisis.

The remainder of our paper proceeds as follows. In Section 2, we review the linear, partial adjustment model of leverage and then develop a two-regime threshold model, accounting for asymmetric capital structure adjustments. Next, we discuss the potential determinants of the SOA to be employed as transition variables under the proposed regime-switching framework. Here, we also discuss how the credit shock triggered by the Global Financial Crisis gives rise to time-varying heterogeneity in the SOA. In Section 3, we briefly describe the estimation and testing procedures. To preserve space, we discuss our econometric methods in detail in a separate technical supplement (available upon request). In Section 4, we report and discuss the empirical results. In Section 5, we provide some concluding remarks.

2 Dynamic Capital Structure Adjustment Models

2.1 Linear and Threshold Partial Adjustment Models of Leverage

2.1.1 Linear Partial Adjustment Model

To test the dynamic trade-off theory’s prediction that firms adjust toward target leverage in the long-run, extant empirical research has used the following partial adjustment model of leverage (e.g., Flannery and Rangan, 2006):

$$\Delta d_{it} = \lambda (d_{it}^* - d_{it-1}) + v_{it}, \quad (1)$$

where d_{it} is the actual leverage ratio and d_{it}^* is the target leverage ratio;² v_{it} is an error component such that $v_{it} = \mu_i + e_{it}$, where μ_i is the (unobserved) firm fixed effects which capture unique industry- and firm-specific characteristics. e_{it} is the idiosyncratic error term with zero mean and constant variance. λ is the SOA, which varies between 0 and 1 due to the presence of positive adjustment costs. The magnitude of the SOA is the key subject of empirical capital structure studies because it indicates how fast firms move toward their target leverage. Thus, it sheds light on the question of whether firms follow the trade-off theory's prediction. In the empirical work below, we first estimate this model before focusing on the threshold partial adjustment model.

Note that in (1), target leverage is unobserved. However, this target ratio can be proxied by a function of firm-specific characteristics, as follows:

$$d_{it} = d_{it}^* + u_{it} = \beta' \mathbf{x}_{it} + u_{it}, \quad (2)$$

where \mathbf{x}_{it} is a $k \times 1$ vector of the determinants, β is a vector of the corresponding coefficients, and u_{it} is the error term with zero mean and constant variance. Based on previous research (e.g., Flannery and Rangan, 2006; Byoun, 2008), we include in this target leverage model the most widely-used determinants of leverage, namely profitability, growth opportunities (the market-to-book ratio), depreciation, firm size, tangibility, R&D expenses and the R&D dummy variable, and the industry median of leverage.³

Based on (1) and (2), we employ a two-stage procedure typically used in the literature to estimate the SOA (e.g., Fama and French, 2002; Byoun, 2008; Faulkender et al., 2012). First, we regress actual leverage on the determinants in (2) and obtain the fitted values as proxies for target leverage, $\hat{d}_{it}^* = \hat{\beta}' \mathbf{x}_{it}$, where $\hat{\beta}$ is the consistent estimate of β . Second, given the (estimated) target leverage, \hat{d}_{it}^* , we estimate the SOA, λ , in (1). Note that an alternative approach is to substitute (2) into (1), thus obtaining the following model that can be estimated in one stage (e.g., Ozkan, 2001; Flannery and Rangan, 2006):

$$d_{it} = \phi d_{it-1} + \gamma' \mathbf{x}_{it} + v_{it}, \quad (3)$$

where $\phi = 1 - \lambda$ and $\gamma = \lambda \beta$. In one-stage estimation, the SOA and target leverage relationships are

²Following previous research (Fama and French, 2002; Chang and Dasgupta, 2009), we measure leverage by the book leverage ratio.

³To avoid a potential endogeneity problem, in our empirical work we include the lagged values of these variables.

estimated jointly such that $\hat{\lambda} = 1 - \hat{\phi}$ and $\hat{\beta} = \hat{\gamma} / (1 - \hat{\phi})$. In estimating the linear, partial adjustment model (1), we consider both the one- and two-stage estimation approaches.

2.1.2 Dynamic Threshold Partial Adjustment Model

Using the linear, partial adjustment model (1) assumes symmetry in capital structure adjustment such that the speed with which firms adjust toward target leverage is homogeneous. However, this assumption is questionable because firms have different degrees of financial constraints and thus do not adjust in the same manner. As mentioned, firms only adjust their capital structures when the costs of adjustment are more than offset by the benefits of being close to target leverage (Fischer et al., 1989). It follows that firms with high levels of financial constraints may face higher adjustment costs, resulting in potentially slower adjustment. In contrast, firms with good access to the external capital markets should have the capability to adjust their capital structures quickly. In addition, firms may take different adjustment paths according to the position of their actual leverage relative to target leverage. Assuming a fixed adjustment cost function, firms should adjust their capital structures more frequently at the lower or upper thresholds of the target leverage range. The larger the deviation from the target, the faster the SOA. However, when firms have a proportional adjustment cost function (Leary and Roberts, 2005), an opposite prediction can be reached. In this case, firms with actual leverage deviating from target leverage may find it costly to revert to the target, so that their adjustment is small in magnitude and takes place more slowly.

The above arguments simply suggest that firms' adjustment speeds should be different, according to their degrees of financial constraints, or their positions relative to target leverage (i.e., target leverage deviation). To account for such (cross-sectional) asymmetry in capital structure adjustment, we employ the following threshold partial adjustment model:

$$\Delta d_{it} = \lambda_1 (d_{it}^* - d_{it-1}) 1_{(q_{it} \leq c)} + \lambda_2 (d_{it}^* - d_{it-1}) 1_{(q_{it} > c)} + v_{it}, \quad v_{it} = \mu_i + e_{it}, \quad (4)$$

where $1_{(\cdot)}$ is an indicator function used to divide firms into two financing regimes, conditional on the (regime-switching) transition variable, q_{it} , which captures differences in firms' adjustment costs (see Section 2.2 for detailed discussions of several candidates for this variable). Firms are categorized into the low regime if $q_{it} \leq c$ and into the high regime if $q_{it} > c$,⁴ and c is the threshold parameter that will

⁴It is in theory straightforward to develop threshold models with multiple regimes, although, practically, the larger the

be estimated within the model rather than being imposed *ex ante*.⁵

Model (4) improves on the linear, partial adjustment model, (1), in one crucial aspect: it explicitly allows for (cross-sectional) asymmetry in capital structure adjustment, and more specifically, heterogeneity in the SOA for firms under two different financing regimes. Further, our modeling has an important advantage over the typical approach used in recent research to study asymmetric adjustment based on sample-splitting or dummy variables (e.g., Byoun, 2008). While the sample-splitting or dummy variable approach selects regimes in an ad-hoc and arbitrary manner *ex ante* (e.g., the median or quartiles), our model allows the threshold parameter to be estimated within the model (Hansen, 2000). Thus, our approach completely avoids any arbitrariness in choosing threshold values that may lead to nontrivial estimation biases in the SOA and inference complexities in testing for the threshold effects, problems that may affect the conclusions drawn.

2.2 Regime-switching Variables and Determinants of the Speed of Adjustment

In this subsection, we discuss several candidates for the (regime-switching) transition variable, q_{it} , in the threshold dynamic panel model of leverage, (4).

2.2.1 Single Firm-specific Variables

Growth Opportunities. The effect of growth opportunities on the SOA is ambiguous. Firms having high growth prospects tend to be young, with limited profitability, and retained earnings, so that they must rely mainly on external funds to finance their investments. Frequent visits to the external capital markets mean that the costs of leverage adjustment are relatively smaller as they can be shared with the costs of issuing securities (Faulkender et al., 2012). More importantly, through external financing activities, high-growth firms can choose an appropriate mix of debt and equity to quickly close out any deviations from their target leverage (Drobetz et al., 2006; Dang et al., 2012). This argument suggests that growth opportunities and the SOA have a positive relation. However, a counter-argument can be made. Firms with limited growth options tend to operate in mature industries and face a low cost of capital. Accordingly, these firms may adjust their capital structures more rapidly than their high-growth

number of regimes, the heavier the computational burden, and the more complex the inference. In unreported experiments, we found (statistically) insignificant results in favor of three over two regimes.

⁵Recent empirical research in corporate finance has employed an alternative approach based on the Maddala and Nelson (1994) endogenous switching model. See, for example, Almeida and Campello (2007) and Hanousek and Shamshur (2011). However, this approach is most applicable to static panel data models and has not yet been extended to the general case of dynamic models, such as the partial adjustment model considered in our study.

counterparts. Moreover, low-growth firms with large free cash flows tend to adopt a high-leverage policy to alleviate overinvestment problems (Jensen, 1986); yet high leverage with potentially high financial distress costs may provide these firms with strong incentives to adjust their capital structures, especially when they are over-levered. These arguments predict that growth opportunities and the SOA are inversely related.

Firm Size. Large firms generally have better access to external sources of financing than small firms because they face lower degrees of asymmetric information and agency problems (Drobetz et al., 2006). They also tend to be more mature with higher asset tangibility and profitability, and so face lower leverage adjustment costs. These arguments suggest that firm size and the SOA are positively related. However, larger firms may use more public debt that is costly to adjust (Flannery and Rangan, 2006). Further, they may be under less pressure to attain target leverage thanks to lower financial distress costs, less cash flow volatility, and fewer debt covenants (Dang et al., 2012). Put differently, large firms may have less incentive to adjust their capital structures due to lower opportunity costs of deviating from the optimal levels (Elsas and Florysiak, 2011). Hence, an alternative prediction is that large firms have a slower SOA than small firms.

Investment. Firms with large capital expenditure may need to raise funds externally, which provides them with an opportunity to adjust their capital structures appropriately as the adjustment costs can be shared with the costs of external financing (Faulkender et al., 2012). The implication follows that investment and the SOA are positively related. However, if capital spending is mostly funded by internally generated funds (e.g., Myers, 1984), it may reduce the retained earnings available for (internal) leverage adjustment (e.g., share repurchases or debt retirements). This alternative argument suggests a negative impact of investment on the SOA.

Earnings Volatility. Firms with volatile earnings typically face borrowing constraints due to the risk of them not generating sufficient earnings to meet debt commitments (Antoniou et al., 2008). As these firms have limited access to the external capital markets, they are likely to make slower adjustment toward target leverage (Dang et al., 2012). Hence, we expect earnings volatility and the SOA to be inversely related.

2.2.2 Composite Measures of Financial Constraints and Target Leverage Deviations

The SA index. One of our main arguments has been that financially constrained firms, such as small and high-growth firms and those with volatile earnings, are likely to adjust their capital structures more slowly than their unconstrained counterparts.⁶ However, the single firm characteristics discussed above only provide indirect and incomplete measures of financial constraints. To address this limitation, we consider a direct, composite measure of external financial constraints.⁷ Following Hadlock and Pierce (2010), we use the SA index, a linear combination of firm size and age.⁸ Firms with low SA scores are less financially constrained than those with high scores. We thus expect the former firms to have lower adjustment speeds than the latter firms. In short, the SOA should be inversely related to the SA index.

Deviations from Target Leverage. Dynamic trade-off models suggest that a firm does not always adjust its capital structure. The firm may allow its leverage to deviate from a target as long as the costs of adjustment outweigh the opportunity costs of deviation (Fischer et al., 1989; Leland, 1994). If fixed costs (e.g., listing, registration, and underwriting fees) are a major component of the adjustment costs, the larger the deviation, the greater the incentive for the firm to make the adjustment. There will be some lower or upper bounds where the benefits of operating at target leverage outweigh the fixed costs of adjustment. At those restructuring thresholds, capital structure adjustment takes place more quickly, implying a positive relationship between the (absolute) target leverage deviation and the SOA.

However, if adjustment costs are an increasing function of the target leverage deviation, i.e., a proportional cost function (Leary and Roberts, 2005), we may reach a conflicting prediction.⁹ A firm with a large deviation from its target leverage may find it costly to revert to such a target, meaning any adjustment tends to be small in magnitude. Alternatively, when adjustment costs become prohibitively high, firms tend to avoid external adjustment (via security issues), and rely more on internal adjustment (via security repurchases/retirements), which is limited in scope and magnitude (Drobtz et al., 2006).

⁶Recently, Campbell et al. (2012) show that (internal) financing constraints do increase the cost of debt and equity.

⁷We thank the reviewer for this suggestion.

⁸Hadlock and Pierce (2010) show that the SA index is a more appropriate measure of financial constraints than just firm size and alternative composite measures, such as the KZ index (Kaplan and Zingales, 1997; Lamont et al., 2001) and the WW index (Whited and Wu, 2006). In (unreported) analysis, we have considered the KZ and WW indices and obtained mixed results. Similarly, we have obtained unsatisfactory results for other commonly used single measures of constraints, including the dividend payout ratio and asset tangibility.

⁹According to Lee et al. (1996), the average total direct costs of seasoned equity offerings are 7.7% of the proceeds, while those of straight debt issues are 2.2%. Economies of scale exist as these costs seem to be negatively related to the total proceeds. However, the larger the size of the security issue, the smaller the economies of scale. For example, the economies of scale are mainly exhausted for straight debt issues with total proceeds exceeding \$40 million. Overall, there is moderate evidence that the adjustment costs are proportional.

Further, firms typically refrain from using all internal funds for adjustment purposes because they wish to preserve their financial flexibility. These arguments point to a negative relationship between the magnitude of target leverage deviation and the SOA.

We use two measures of deviations from target leverage, the absolute deviation level and the absolute deviation ratio. The deviation ratio has an important qualitative advantage over the deviation level. For the purpose of illustration, suppose that the absolute deviation is 20% for two firms A and B, whose target leverage ratios are equal to 25% and 50%, respectively. Estimating the threshold model using the absolute deviation of 20% as the transition variable does not recognize the fact that firm A is deviating considerably from the target leverage with a deviation ratio of 80%, whereas firm B is deviating moderately with a deviation ratio of 40%. The SOA may differ for these two firms, even with the same absolute deviation.

2.3 The Impact of the Global Financial Crisis on the Speed of Adjustment

Our discussion in the previous subsection shows how the SOA can vary cross-sectionally with several firm-specific characteristics and their linear combinations, proxying for the degrees of financial constraints and costs of leverage adjustment. However, the SOA may also vary over time because capital structure adjustment can be affected by the stage of the business cycle, especially by an exogenous credit shock triggered by the Global Financial Crisis of 2007–2009.¹⁰ There are several arguments as to why macroeconomic conditions influence corporate capital structure decisions. First, in the literature on monetary transmission, the balance sheet channel view argues that corporate leverage is pro-cyclical (e.g., Bernake and Gertler, 1989; Kiyotaki and Moore, 1997). The underlying argument is that a firm tends to borrow less during an economic downturn, for the value of its collateral declines, reducing its debt capacity; see also Bernanke and Gertler (1995) for a review. However, the effect of the business cycle variables on a firm's leverage increases with its degree of financial constraint. A constrained firm has greater difficulty borrowing in bad states because of a much larger premium on external funds (e.g., Gertler and Gilchrist, 1993). Empirical research generally shows that corporate capital structure varies with macroeconomic conditions. However, while earlier evidence suggests that leverage is counter-cyclical (e.g., Korajczyk and Levy, 2003), recent evidence shows that, consistent with the balance sheet channel view, debt issues are pro-cyclical, especially for firms facing financial

¹⁰We thank the reviewer for encouraging us to follow this line of inquiry.

constrains and having low credit ratings (Covas and Den Haan, 2011; Erel et al., 2012).

Second, and more importantly, macroeconomic variables affect not only a firm's leverage ratio but also its adjustment toward target leverage (e.g., Drobetz and Wanzenried, 2006; Hackbarth et al., 2006; Cook and Tang, 2010). Hackbarth et al. (2006) show theoretically that firms rebalance their leverage ratios more frequently in economic expansions than in economic recessions. The thresholds for leverage adjustments are higher in recessions because they increase with (proportional) adjustment costs that rise with adverse macroeconomic conditions. Empirically, Cook and Tang (2010) find that between 1977 and 2006, firms adjust toward target leverage faster in good states of the economy when they have access to a greater supply of credits and face lower adjustment costs.

To examine the effects of macroeconomic conditions on capital structure adjustments, we use a negative (exogenous) shock to the supply of credits caused by the Global Financial Crisis of 2007–2009. The crisis, which began in August 2007 as a consequence of subprime mortgage defaults in the US, and the resulting economic recession (from December 2007 to June 2009) had severe effects on financial institutions and non-financial companies. Several recent studies document significant adverse effects of the crisis on corporate financial policies, including a substantially lower supply or higher costs of external finance, a considerable decline in bank borrowings (Ivashina and Scharfstein, 2010), and a significant cutback in investments (Campello et al., 2010; Duchin et al., 2010; Campello et al., 2011). Based on the above theoretical predictions and recent empirical evidence, we hypothesize that firms face higher leverage adjustment costs during the crisis and, as a result, move toward their target leverage at slower rates. Simply put, the Global Financial Crisis has a negative impact on the SOA. Further, such an impact is likely to be greater for firms that are already financially constrained and, thus, face even more limited access to external finance.

3 Methods

In this section, we combine three branches of literature, namely (linear) dynamic panel data models (Alvarez and Arellano, 2003), threshold models in nonlinear time series analysis (Chan, 1993; Hansen, 2000), and threshold models in static panels (Hansen, 1999), to develop estimation and testing procedures for the threshold dynamic panel data model, (4). Next, we propose two approaches to investigate the effects of the global financial crisis on the adjustment speeds.

3.1 Estimating the Threshold Partial Adjustment Model

As in the linear case described in Subsection 2.1, we now adopt the two-stage procedure to estimate the threshold partial adjustment model, (4).¹¹ In the first stage, we estimate (2) to obtain the long-run target leverage $\hat{d}_{it}^* = \hat{\beta}' \mathbf{x}_{it}$. In the second, we estimate the heterogeneous adjustment speeds, λ_1 and λ_2 corresponding to two financing regimes, in (4):

$$\Delta d_{it} = \lambda_1 (\hat{d}_{it}^* - d_{it-1}) 1_{(q_{it} \leq c)} + \lambda_2 (\hat{d}_{it}^* - d_{it-1}) 1_{(q_{it} > c)} + \mu_i + e_{it}, \quad i = 1, \dots, N; t = 2, \dots, T, \quad (5)$$

which can be compactly written as:

$$\Delta d_{it} = \lambda_1 dev_{1it}(c) + \lambda_2 dev_{2it}(c) + \mu_i + e_{it}, \quad (6)$$

where $dev_{1it}(c) = (\hat{d}_{it}^* - d_{it-1}) 1_{(q_{it} \leq c)}$ and $dev_{2it}(c) = (\hat{d}_{it}^* - d_{it-1}) 1_{(q_{it} > c)}$ are the deviations from target leverage for firms in the low and high regimes, respectively, and the μ_i 's are the unobserved firm fixed effects. Note that to mitigate endogeneity concerns, we use the first lagged values of the transition variables.

In estimating λ_1 and λ_2 in (5), the pooled OLS estimator (hereafter POLS) is biased downwards because the two regressors, $dev_{1it}(c)$ and $dev_{2it}(c)$, are correlated with the fixed effects μ_i . Even the fixed effects (hereafter FE) estimator, which wipes out the individual effects, μ_i , from the model, is biased upwards for fixed T (Nickell, 1981).

To avoid this problem, we consider the first-difference transformation of (6):

$$\Delta^2 d_{it} = \lambda_1 \Delta dev_{1it}(c) + \lambda_2 \Delta dev_{2it}(c) + \Delta e_{it}, \quad i = 1, \dots, N; t = 3, \dots, T, \quad (7)$$

which is free of the unobserved fixed effects, μ_i . However, applying the POLS estimator to this first-

¹¹Here we follow conventional theoretical and empirical research in the literature (Fischer et al., 1989; Byoun, 2008; Faulkender et al., 2012), and assume that the long-run target leverage relationships are homogeneous across regimes. Hence, our focus is to compare the (heterogeneous) speeds with which firms adjust toward common long-run target leverage ratios. An alternative way to develop the threshold partial adjustment model of leverage is to substitute (2) into (5) to yield:

$$d_{it} = (\phi_1 d_{it-1} + \gamma_1' \mathbf{x}_{it}) 1_{(q_{it} \leq c)} + (\phi_2 d_{it-1} + \gamma_2' \mathbf{x}_{it}) 1_{(q_{it} > c)} + \mu_i + e_{it}.$$

Dang et al. (2012) consider this one-stage estimation approach and allow both the SOA and the long-run target leverage relationships to be heterogeneous under different regimes. Note, however, that it is much more complex to estimate this model under the assumption of common target leverage, which imposes the following nonlinear restrictions: $\beta_1 = \beta_2$ where $\beta_j = -\gamma_j/\phi_j$, $j = 1, 2$.

difference model still produces biased estimates of the SOA because $\Delta dev_{1it}(c)$ and $\Delta dev_{2it}(c)$ are correlated with Δe_{it} via the correlation between $d_{i,t-1}$ and $e_{i,t-1}$. To address this crucial issue, we follow the literature and consider using instrumental variable (henceforth IV) and GMM estimators. Specifically, we need to find instruments for $\Delta dev_{1it}(c)$ and $\Delta dev_{2it}(c)$ in (7) that satisfy the orthogonal condition with Δe_{it} . Two possible candidates are $dev_{1i,t-1}(c)$ and $dev_{2i,t-1}(c)$, as suggested by Anderson and Hsiao (1982); we refer to this method AH-IV. Although the AH-IV estimator is consistent, it lacks efficiency.

To improve the efficiency of the estimates, we extend Arellano and Bond's (1998) linear GMM estimator and consider $dev_{1i,t-1}(c)$ and $dev_{2i,t-1}(c)$, where $dev_{1i,t-1}(c) = (\hat{d}_{i,t-1}^* - d_{i,t-2}) 1_{(q_{it} \leq c)}$ and $dev_{2i,t-1}(c) = (\hat{d}_{i,t-1}^* - d_{i,t-2}) 1_{(q_{it} > c)}$, and their deeper lagged values as instruments for $\Delta dev_{1it}(c)$ and $\Delta dev_{2it}(c)$, where $\Delta dev_{1it}(c) = (\Delta \hat{d}_{it}^* - \Delta d_{i,t-1}) 1_{(q_{it} \leq c)}$ and $\Delta dev_{2it}(c) = (\Delta \hat{d}_{it}^* - \Delta d_{i,t-1}) 1_{(q_{it} > c)}$ in (7).¹² We are then able to construct the matrix of the full GMM instruments, denoted $\mathbf{W}(c)$, and derive the one- and two-step GMM estimators, $\hat{\lambda}_s(c)$, with $s = GMM1, GMM2$, for a given threshold, c . We provide a detailed derivation of these GMM estimators in a separate technical supplement.

Next, we estimate the threshold parameter, c , consistently by using a grid search over the support of the transition variable, q_{it} , that minimizes a generalized distance measure, such that:

$$\hat{c} = \underset{c \in \mathcal{C}}{\operatorname{argmin}} Q(c). \quad (8)$$

where \mathcal{C} is the grid set and $Q(c)$ is the generalized distance measure, given by:

$$Q(c) = \left\{ \frac{1}{N} \mathbf{W}(c)' \Delta \hat{\mathbf{e}}(c) \right\}' \left\{ \frac{1}{N} \hat{\mathbf{V}}_{GMMs}(c) \right\}^{-1} \left\{ \frac{1}{N} \mathbf{W}(c)' \Delta \hat{\mathbf{e}}(c) \right\}, \quad s = 1, 2, \quad (9)$$

where $\Delta \hat{\mathbf{e}}(c) = \Delta^2 d - \Delta \mathbf{dev}(c) \hat{\lambda}_s(c)$, $\mathbf{W}(c)$ is the matrix of the GMM instruments, and $\hat{\mathbf{V}}_{GMMs}(c)$ is the estimated covariance matrix in the s -step GMM regression, where $s = 1, 2$. Note that because the model is linear in λ for each c , our grid search algorithm should produce a consistent estimate of the threshold value, \hat{c} . For practical reasons, such as to avoid the effects of extreme values, our grid set, \mathcal{C} , is restricted between the 15th and 85th percentiles of the transition variable. Chan (1993) shows under the assumption of exogenous transition variables that the threshold estimate, \hat{c} , is super-consistent, though its asymptotic distribution is complex and depends on nuisance parameters. However, this

¹²We use the first lagged values $dev_{1i,t-1}(c)$ and $dev_{2i,t-1}(c)$ as instruments because they are correlated to the independent variables but not included in the dynamic model (7), and not correlated to the error term in first differences, Δe_{it} .

finding is not useful for inference in practice. Hence, we follow Hansen (1999, 2000), and construct the confidence interval for \hat{c} by forming the non-rejection region using the LR statistic for the null hypothesis, $H_0 : c = c_0$.

Finally, it is important to assess the (potential) impact of \hat{d}_{it}^* , the estimated regressor of d_{it}^* from (2), on the GMM estimators of the SOA, λ in (6). It is well established in the econometrics literature that $\hat{\lambda}$, the two-stage estimator of λ , will be asymptotically efficient, and no asymptotic efficiency gains are available by switching to a full MLE of (2) and (5) simultaneously, though the least-square estimator of the variance of $\hat{\lambda}$ is potentially inconsistent (e.g., Pagan, 1984). However, for any given threshold parameter, c , and for large N , the two-step GMM estimator is consistent and asymptotically normally distributed with the covariance matrices consistently estimated (see Newey, 1984; Hall, 2005, and also the technical supplement). Hence, in our empirical analysis, we adopt the two-step GMM estimator to take advantage of its superior efficiency and robustness.¹³

3.2 Testing for Threshold Effects

We briefly outline our procedure to test the null hypothesis of no threshold effect (homogeneous SOA) in (4) against the alternative hypothesis of a threshold effect (heterogeneous SOA). Formally, we set the null hypothesis as:

$$H_0 : \mathbf{R}\lambda = 0, \quad (10)$$

where $\mathbf{R} = (1, -1)$ and $\lambda = (\lambda_1, \lambda_2)$. We then consider the following Wald statistic:

$$\mathcal{W}(\hat{c}) = \left\{ \mathbf{R}\hat{\lambda}(\hat{c}) \right\}' \left\{ \widehat{\mathbf{RVar}}\left(\hat{\lambda}(\hat{c})\right) \mathbf{R}' \right\}^{-1} \left\{ \mathbf{R}\hat{\lambda}(\hat{c}) \right\}, \quad (11)$$

where $\hat{\lambda}(\hat{c})$ is the GMM estimator. It is straightforward to evaluate the Wald statistic for each c using the (asymptotic) variance estimates. See our supplement for more details. However, inference is non-standard due to the well-established problem that the (nuisance) threshold parameter, c , is not identified under the null (Davies, 1987; Andrews and Ploberger, 1994, 1996; Hansen, 1996). To overcome this

¹³The GMM estimator and the associated bootstrap-based testing procedure, as discussed in the next subsection, are implemented using Stata codes based on *xtabond2* (Roodman, 2009). Based on Blundell and Bond's (1998) system GMM (SYSGMM) for (non-threshold) dynamic panels, we have also developed the SYSGMM estimator for the threshold (non-linear) case (the detailed derivation of which is available upon request). However, we do not use this method in our empirical work below because the validity of the SYSGMM instruments is strongly rejected at the 1% level for all cases considered. The over-fitting bias problem seems to be more serious in dynamic panel threshold models.

problem, we follow Hansen (1996, 1999) and obtain a valid asymptotic p -value of the statistic using a bootstrap technique. We describe this bootstrap-based testing procedure in detail in our technical supplement. We have also conducted Monte Carlo simulation exercises to investigate the performance of the GMM estimators and inferences in two-stage estimation, especially in the presence of generated regressors. The simulation results reported in our supplement show that the two-step GMM estimator is reasonably precise. Moreover, the bootstrap-based Wald test for threshold effects has almost negligible size distortion, and sufficiently high power.

3.3 Examining the Impact of the Global Financial Crisis

To examine the effects of the Global Financial Crisis on the SOA, we adopt two approaches. First, we add a dummy variable that proxies for the effects of the crisis to the linear partial adjustment model (1):

$$\Delta d_{it} = (\lambda + \lambda_{FC} D_t) dev_{it} + v_{it}, \quad (12)$$

where the dummy variable, D_t , takes the value of 1 if the year in question is a crisis year (between 2007 and 2009), and 0 otherwise. The regressor, $dev_{it} = d_{it}^* - d_{it-1}$, is the deviation from target leverage. The SOA is equal to λ in the noncrisis years and $\lambda + \lambda_{FC}$ in the crisis years (2007–2009). According to our hypothesis, we expect a negative impact of the crisis on the SOA, i.e., $\lambda_{FC} < 0$.

A drawback of the dummy-variable approach is that it implicitly assumes homogeneity in the long-run relationships between target leverage and its determinants, regardless of the period under investigation (crisis versus noncrisis). Hence, we next employ an alternative approach in which we allow the long-run target leverage relationships to change during the crisis period. Specifically, we examine two subperiods, a pre-crisis period between 2002 and 2006 and a crisis period between 2006 and 2010.¹⁴ For each subperiod, we estimate the linear partial adjustment model (1) and test whether the SOA declines during the crisis period.

Note that the above sample-splitting analysis only allows for time-varying heterogeneity in the SOA, the heterogeneity caused by the crisis. To examine a more realistic scenario under which the SOA also varies with the (regime-switching) transition variables, as discussed in Subsection 3.2, we

¹⁴According to the National Bureau of Economic Research (NBER), there was an economic recession between March and November 2001. We thus consider the pre-crisis period from 2002 in order to avoid the impact of this economic downturn.

employ the threshold model (5) for each subperiod. That is, we estimate the threshold and the SOA for each regime-switching variable, for the pre-crisis and crisis periods, respectively. Due to the short length of our sample period and the low frequency of the (annual) data, we impose the time-series thresholds rather than estimating them. The main aim of this analysis is to determine whether there exists cross-sectional heterogeneity in the SOA conditional on the regime-switching variables, even after accounting for the effects of the Global Financial Crisis.

A potential limitation of our subperiod analysis is that our crisis period (2006–2010) covers two non-crisis years 2006 and 2010, of which the year 2006 is also overlapping with the pre-crisis period (2002–2006). However, it is not possible to restrict the crisis period to 2007–2009, as in the dummy-variable approach above, because the GMM regressions for each subperiod require at least five firm-year observations (Arellano and Bond, 1991). Note that including two non-crisis years in the crisis period may affect the accuracy of the SOA estimates. To address this limitation and the arbitrariness in specifying subperiods, we conduct a rolling-regression analysis in which we estimate both the linear and threshold, partial adjustment models (1) and (5), using a series of five-year subsamples. The first subsample is 2002–2006 and the last subsample is 2008–2012, with a rolling window of one year. This analysis allows us to examine the evolution of the (heterogeneous) SOA over the sample period 2002–2012.

4 Data and Empirical Results

4.1 Data and Sample Selection

We collect annual financial and accounting data for US publicly listed firms from the *Compustat* database for the period 2002–2012. Our sample period is reasonable because it covers the Global Financial Crisis and so enables us to examine the effects of the crisis on capital structure adjustment. As mentioned above, our sample starts from 2002 so as to avoid the collapse of the dot-com bubble (1999–2000) and the economic recession (2001). Our relatively short sample length (11 years in total) also helps to reduce heavy computational burden required in the grid search for the threshold value and, in particular, the bootstrap-based threshold test. We apply the following standard restrictions on our data (Flannery and Rangan, 2006; Byoun, 2008). First, we remove financial firms (SIC codes 6000–6999) and utilities (SIC codes 4900–4999) because they are subject to different accounting con-

siderations. Second, we remove firms that have fewer than five years of observations so that we can use the GMM estimators that require the use of lagged instruments (Arellano and Bond, 1991). Third, we also remove observations that have missing data. Finally, we winsorize all variables at the 1st and 99th percentiles to mitigate the impact of extreme outliers (Flannery and Rangan, 2006). Our sample comprises 6,232 companies and 51,894 firm-year observations. In Table 1, we provide the summary statistics for the variables of interest.

Table 1 about here

4.2 Regression Results for the Linear Partial Adjustment Model

Table 2 reports the regression results for the static model of target leverage (2) and the (linear) dynamic model of leverage adjustment (3). The static model is estimated with the POLS and FE estimators. The partial adjustment model is estimated with two dynamic panel data methods, the AH-IV and GMM estimators.¹⁵ We include time dummies in our dynamic model (3) to control for changes in common macroeconomic conditions that affect corporate capital structures (e.g., Flannery and Rangan, 2006). We report the AR(2) and Sargan test statistics to assess the validity of the instruments used in the dynamic models.

Table 2 about here

The results for the target leverage model (2) reported in columns (1) and (2) show that profitability has a significantly negative effect on target leverage, which is consistent with both the pecking order theory (Myers and Majluf, 1984; Myers, 1984) and dynamic trade-off models (e.g., Strebulaev, 2007), as well as previous empirical evidence (Titman and Wessels, 1988; Rajan and Zingales, 1995). Growth opportunities and target leverage have a positive relation, which is in line with the pecking order view (e.g., Frank and Goyal, 2007). This finding is, however, inconsistent with the agency arguments that high-growth (low-growth) firms use less (more) leverage to alleviate underinvestment (overinvestment) incentives (Myers, 1977; Jensen, 1986). Depreciation has a significantly positive effect on target leverage, which is inconsistent with the view that non-debt tax shields (such as depreciation) can substitute for debt tax shields (DeAngelo and Masulis, 1980). However, this finding may be driven by the correlation between depreciation and tangibility (fixed assets), which has a strong positive impact on target

¹⁵Note that the GMM estimator used here is for the linear case, as opposed to the estimator for the more general, non-linear case developed in Subsection 3.1 above.

leverage (Mackie-Mason, 1990). Indeed, the coefficient on tangibility is significantly positive, supporting the argument that tangible assets can be used as a collateral to avoid the asset substitution problem (e.g., Frank and Goyal, 2007). The coefficients on R&D expenses and its dummy variable are either insignificant or significant with an unexpected sign. Finally, consistent with our conjecture, the industry median leverage ratio has a positive effect on target leverage. Overall, the regression results, in particular those obtained with POLS, are reasonable.

In columns (3) and (4), which report the results for the linear partial adjustment model (3), the (implied) SOA estimated with the AH-IV and GMM estimators is 31% and 29%, respectively. These results suggest that US firms adjust their capital structures with moderate speeds: they close out approximately 30% of their deviations from target leverage per year.¹⁶ Our estimates are consistent with recent estimates of the SOA reported in the literature (Lemmon et al., 2008) and provide moderate support for the dynamic trade-off theory.

We next estimate the partial adjustment model using the two-stage procedure based on (1) and (2). In Table 3, we report the results obtained using four alternative estimators, including two traditional, yet biased methods for dynamic panels (i.e., POLS and FE) and two advanced and unbiased methods (i.e., AH-IV and GMM).¹⁷ The POLS and FE estimates of the SOA are 18% and 53%, respectively, which are clearly biased downwardly and upwardly, as expected. Turning to the consistent estimates obtained with AH-IV and GMM, the SOA is 33% and 31%, respectively. These results are in line with the one-stage estimation results and again show that US firms, on average, adjust toward target leverage at moderate rates.¹⁸ Overall, our one-stage and two-stage results provide robust evidence for the trade-off theory.

Table 3 about here

The results discussed so far assume that firms adjust their capital structures in a symmetric manner

¹⁶Using the concept of “half life”, these estimates indicate that it takes 1.94 years for deviations from target leverage to be halved.

¹⁷To compute the target leverage ratio used in the second stage, we employ the POLS estimates reported in column (1) of Table 2. We choose the POLS model over the FE model because the POLS results seem to be more appropriate than the FE results. Specifically, in the FE model, growth opportunities, firm size, and the industry median leverage ratio, three of the five most important determinants of target leverage (Frank and Goyal, 2009), are only weakly significant. The FE regression also has a lower (adjusted) R-squared than the POLS regression (0.11 versus 0.17). Moreover, in subsequent analysis, we find that the FE regression results for the pre-crisis and crisis periods are even more implausible with many insignificant coefficients; see Table A.2 in the supplement. Hence, although recent research suggests estimating target leverage with the firm fixed effects (Hovakimian and Li, 2011), we are unable to follow this approach due to the unsatisfactory FE results.

¹⁸In the GMM regression, the validity of the instruments used is questionable because the Sargan test is rejected (though the AR(2) test is not rejected). Thus, the AH-IV estimate seems more reliable than the GMM estimate.

and at a homogeneous rate. We now turn to discuss the empirical results obtained from the proposed dynamic panel threshold model of leverage, (6).

4.3 Regression Results for the Threshold Partial Adjustment Model

Tables 4 and 5 report the regression results for the threshold partial adjustment model, (5). Specifically, Table 4 contains the results for four single firm-specific transition variables, namely growth opportunities, investment, firm size, and earnings volatility. Table 5 presents the results for three (composite) indices, proxying for financial constraints and deviations from target leverage. Panel A of each table reports the SOA estimates obtained using the two-step GMM estimator for the low and high regimes, where in the low (high) regime, the value of the transition variable is less than (greater than) the estimated threshold value. The panel also contains information about the threshold value estimates (in value and in percentage) and their 99% confidence intervals.¹⁹ Panel B summarizes the most relevant characteristics of firms that are categorized into the low and high regimes. We use the *t*-test to ascertain whether these characteristics are statistically different from each other.

4.3.1 Results for Single Firm-Specific Variables

The results in Panel A of Table 4 suggest that firms with higher growth opportunities, larger capital expenditure, smaller sizes, and more volatile earnings tend to have higher adjustment speeds than those with the opposite characteristics. However, the differences in the SOA estimates are fairly small in magnitude, varying from 2.5% to 7.2%. More importantly, they are only significant for two transition variables, investment and earnings volatility, where the threshold (Wald) test under the null of no threshold effect is rejected at 1% and 5%, respectively. In columns (1)–(2), firms with large investment adjust at a rate of 36% per year, while those with small investment adjust at a rate of 30% per year. The difference of 6% in the SOA is moderate in magnitude but is statistically significant. Our finding does not support the financial constraint view that firms with large investment, potentially funded by retained earnings, may face internal financial constraints, thus having difficulty making (internal) capital structure adjustment. However, it is in line with the argument that firms with large capital expenditure have greater opportunities to choose an appropriate mix of new debt and equity, especially

¹⁹In unreported analysis, we have also considered the AH-IV estimator. However, for brevity, we only focus on the GMM estimator here. Although both estimation methods are consistent, the GMM estimator is more efficient when the instruments are valid (Arellano and Bond, 1991) and, as mentioned in the previous section, produces a valid procedure for testing the threshold effect.

when their investment is financed externally. These firms can adjust their capital structures faster as they face potentially lower adjustment costs that can be shared with the costs of external funds (Faulkender et al., 2012).²⁰ Turning to Panel B, we find that, consistent with this cost-sharing argument, firms with large capital spending have substantial cash flows and financing deficits, which they offset through external financing, especially equity issues. Further, although these firms have relatively lower leverage and are under-levered, they have significantly larger deviations from target leverage.²¹ The latter finding is in line with our prediction that firms deviating considerably from their target leverage have stronger incentives to adjust their capital structures.

Table 4 about here

In column (7)–(8), firms with more volatile earnings adjust toward target leverage significantly more quickly than those with less volatile earnings. Specifically, the former firms have a SOA of 34%, while the latter have a lower SOA of 27%. This finding is surprising because firms with high earnings volatility tend to face borrowing constraints and have less scope for capital structure adjustment. Empirically, it is inconsistent with recent evidence of the negative relationship between earnings volatility and the SOA (Dang et al., 2012). An inspection of the firm-specific characteristics in Panel B suggests that firms with volatile earnings have significantly lower leverage, as expected. However, they have larger target leverage deviations, hence stronger incentives to adjust their capital structures. This finding is in line with dynamic capital structure adjustment in the presence of a fixed cost function. Finally, these firms rely heavily on external funds (mainly equity issues) to offset their large financing deficits, which, as argued above, provides them with greater opportunities to find an appropriate mix of debt and equity.

4.3.2 Results for Composite Measures of Financial Constraints and Target Leverage Deviations

Turning to Table 5, the results regarding three composite transition variables, namely the SA index and the absolute target leverage deviation (in both levels and ratios) are mixed. Firms with low SA scores and small (absolute) deviations tend to have smaller adjustment speeds than those with the opposite characteristics. However, we only find evidence of a threshold effect when using the absolute

²⁰Although this argument too applies to firms with high growth options that require external financing, in column (1), we find no evidence of a statistically higher SOA for such firms.

²¹A firm's deviation from target leverage is the difference between its observed leverage and target leverage where the target leverage is estimated using the POLS results in column (1) of Table 2. A positive (negative) deviation suggests that the firm is over-levered (under-levered) relative to its target leverage.

deviation ratio as the transition variable. Specifically, in columns (5)–(6), firms with a larger deviation ratio have a SOA of 36%, while those with a small deviation ratio have a lower SOA of 31%. This finding is consistent with dynamic leverage rebalancing in the presence of a proportional adjustment cost function. A firm deviating from its target leverage may find it costly to revert to the target so adjustment tends to be small in magnitude, implying a slower SOA. It is, however, inconsistent with the observations above that firms with a higher SOA tend to have larger target leverage deviations. We return to this puzzling finding in the subperiod analysis in Subsection 4.4.2.

Table 5 about here

Overall, our results for the full sample provide weak and mixed evidence of cross-sectional heterogeneity in the SOA. Of the seven transition variables considered, we only find significant threshold effects for three variables, namely firm investment, earnings volatility, and the absolute deviation ratio. Additionally, the findings are not consistent with the financial constraint argument. Financially constrained firms, such as those with large investment and volatile earnings, seem to have high adjustment speeds. These firms may adjust their capital structures quickly thanks to lower adjustment costs that can be shared with transaction costs required to raise external funds. On the other hand, our insignificant results regarding growth opportunities and firm size are inconsistent with recent evidence in the literature about the impact of those variables on the SOA (e.g., Dang et al., 2011; Elsas and Florysiak, 2011). Note, however, that the differences between our results and those reported by earlier studies may be due to our novel modeling and testing approach in which we employ a more rigorous threshold model and bootstrap-based test for the threshold effect. Finally, a limitation of the present full-sample analysis is that it does not take into account the potential time-varying heterogeneity in the SOA. Hence, in what follows, we examine this source of heterogeneity in the SOA, with a focus on the effects of the Global Financial Crisis.

4.4 The Impact of the Global Financial Crisis

4.4.1 Regression Results for the Linear Partial Adjustment Model

We first examine the evolution of leverage over the sample period 2002–2012. Figure 1.a shows that, as firms accumulated debt in the run-up to the crisis, the mean and median leverage ratios increased gradually over the period 2005–2008, reaching their peaks in 2008 (25.6% and 19.2%, respectively).

As the crisis intensified in 2008, corporate leveraging stopped and deleveraging began: in two years 2009 and 2010, firms reduced the mean and median leverage ratios by more than 2% to 23.2% and 17.6%, respectively. Over the recent period, 2011–2012, however, firms started to lever up again, using as much debt as they did before the crisis. Overall, our results regarding the procyclical behavior of leverage, especially our evidence of (de)leveraging around the crisis, are consistent with recent evidence on Euro firms reported by the European Central Bank (2012). In Figures 1.b and 1.c, we examine whether the impact of the crisis on a firm’s capital structure varies with the level of financial constraint, measured by firm size and the SA index. We find that both constrained and unconstrained firms leveraged up in the period leading to the crisis, before deleveraging in 2009 and 2010. The only noticeable difference is that, for unconstrained firms (firms with large size and small SA scores), the leveraging and deleveraging seemed more aggressive. This suggests that these firms may be able to adjust their leverage ratios more easily than constrained firms. Our results regarding the procyclical behavior of leverage for small and large firms seem consistent with recent evidence on net debt issues (Covas and Den Haan, 2011).

In Table 6, we investigate the effects of the Global Financial Crisis of 2007–2009 on the SOA. As outlined in Section 3.3, we adopt both the dummy-variable and sample-splitting approaches. In column (1), we employ the first approach and report the results for model (12). The coefficient on the crisis dummy variable, SOA_{FC} , is significantly negative (-0.047), suggesting that firms move toward their target leverage at a slower rate during the crisis. Specifically, the SOA is 34% in the noncrisis years but declines to 29% in the crisis years. This finding supports our prediction that firms have difficulties adjusting their capital structures due to limited access to external finance during the crisis.

Table 6 about here

The above approach relies on the assumption that the relationships between target leverage and its determinants remain unchanged during the crisis period. To relax this assumption, in columns (2) and (3), we estimate the SOA for two subperiods 2002–2006 and 2006–2010.²² We find that the SOA for the pre-crisis period is 38% and the SOA for the crisis period is 14%. The difference in the two adjustment speeds (24%) is considerably greater than the difference (5%) estimated using the dummy-variable approach. These results indicate that employing the dummy-variable approach, which

²²For brevity, we report the regression results for the target leverage model for the subperiods in Table A.2 of our supplement.

assumes homogeneous target leverage relationships, is likely to underestimate the effects of the Global Financial Crisis.

Robustness Checks: Rolling-regression Analysis

To examine the robustness of the results, we perform a series of rolling regressions for seven five-year subsamples, starting from 2002–2006 to 2008–2012. As mentioned, the minimum length of each subsample is five years because we run GMM regressions that use lagged instruments. We summarize the SOA estimates in Figure 2. The results reveal a clear downward trend in the SOA around the crisis period. Between 2003 and 2010, the SOA gradually decreases, reaching a trough during the 2006–2010 period. It seems to increase over the period 2007–2011 and, in particular, the most recent period 2008–2012, which consists of four post-crisis years (2009–2012). Overall, our rolling regression analysis corroborates the evidence of the impact of the crisis on the SOA reported in Table 6. Taken together, these findings suggest that the heterogeneous SOA estimates reported in Subsection 4.3 are unreliable because they are time-invariant and as such do not properly account for a structural break due to the Global Financial Crisis. Hence, we next reestimate the threshold model (6), thereby allowing for both cross-sectional (regime-switching) and time-varying asymmetries in the SOA.

Figure 2 about here

4.4.2 Regression Results for the Threshold Partial Adjustment Model

In Tables 7 and 8, we estimate the threshold, partial adjustment model (6) for two subperiods, a pre-crisis period (2002–2006) and a crisis period (2006–2010). Table 7 reports the regression results for growth opportunities, investment, size, and earnings volatility. Table 8 presents the results for the SA index as well as the (absolute) deviation, in levels and ratios. In each table, we report the results for the pre-crisis period in Panel A and the results for the crisis period in Panel B. As in Tables 4 and 5, in each panel we present the estimation and test results, as well as the relevant firm-specific characteristics of firms that are categorized into the low and high regimes.

Results for Single Firm-Specific Variables

The results in Panel A of Table 7 provide strong evidence of threshold effects for all the transition variables under consideration. Specifically, during the pre-crisis period 2002–2006, firms with high growth

opportunities, with large investment, of small size, and with volatile earnings have higher adjustment speeds than those with the opposite characteristics. The differences in the SOA estimates, in the range of 12%–18%, are both economically and statistically significant, with the statistical significance confirmed by the threshold (Wald) test results. Compared with the full-sample results, these differences are markedly larger in magnitude, revealing a greater degree of cross-sectional heterogeneity in the SOA during the pre-crisis period. Nevertheless, as in the full-sample analysis, our findings are inconsistent with the financial constraint argument, because more constrained firms, such as high-growth and small firms and those with large investments and volatile earnings, adjust their capital structures more rapidly than their less constrained counterparts. Our findings seem more in line with the cost-sharing argument (Faulkender et al., 2012). Firms have higher SOA thanks to lower leverage adjustment costs that they can share with the transaction costs of accessing capital markets. Indeed, we find that firms with higher SOA estimates have larger financing deficits, which they offset by raising external funds, equity finance in particular. In addition, these firms have significantly larger leverage (except for firms with large investment) and larger target leverage deviations, hence potentially stronger incentives to revert to their target leverage.

Table 7 about here

Turning to Panel B of Table 7, we find that, during the crisis period, the threshold effect becomes less pronounced for two transition variables, investment and firm size, where the threshold test is marginally rejected at 10%. Further, there is no threshold effect for the remaining variables, growth opportunities and earnings volatility. Compared with the results in Panel A, the adjustment speeds in both the low and high regimes seem to decline, which is consistent with the evidence of the negative impact of the Global Financial Crisis documented in the previous subsection. Next, comparing the firm characteristics in Subpanel B2 with those in Subpanel A2, we find that firms generally adjust at slower rates because their external financing activities (net debt and equity issues) are curtailed during the crisis. In some cases, firms not only reduce their net equity issued but also retire their debt, possibly because they have to cut back investments (see columns (1) and (3) for firms with low growth and capital expenditure). Note, however, the magnitude of the decrease in the SOA is regime-dependent. Firms with high growth, with large capital expenditure, of small size, and with earnings volatility experience a much larger decline in their adjustment speeds (in the range of 21%–29%). On the other hand, firms with the opposite characteristics (i.e., those with low growth, with small investment, and

of large size) see a more moderate drop in their SOA estimates (in the range of 18%–21%); the only exception is firms with less earnings volatility, which experience a nontrivial decrease in the SOA (see column (7)). The crisis exerts stronger effects on firms with higher SOA estimates possibly because these firms are more constrained. These findings support our conjecture that the impact of the Global Financial Crisis on a firm's SOA increases with the degree of financial constraint facing the firm.

Results for Composite Measures of Financial Constraints and Target Leverage Deviations

In Panel A of Table 8, the SOA appears to be higher for firms with higher SA scores and smaller deviations from target leverage (in both levels and ratios). However, we only document evidence of asymmetry in the SOA conditional the SA index, as the threshold test is rejected at 1%. For the deviation variables, the differences in the SOA are statistically insignificant as the threshold tests are not rejected. These results are, thus, in conflict with the full-sample results reported in Table 5, in which the SOA varies with the deviation ratio, but not with the SA index. This again suggests that the full-sample results are likely to be misleading and must be taken with caution. Next, focusing on the SA index, the finding that firms with high SA scores (i.e., more constrained firms) adjust their capital structures more quickly than those with low scores (i.e., less constrained firms) corroborates our earlier results and provides direct evidence against the financial constraint argument. A closer inspection of the firm-specific characteristics reveals the same pattern documented in the previous subsections: firms with higher SOA estimates tend to have much larger financing gaps, which they cover by actively raising external funds. This observation is more consistent with the cost-sharing argument that the leverage adjustment costs are relatively lower when they are shared with the costs of external finance.

Table 8 about here

Panel B of Table 8 shows that in the crisis years, most firms experience a decline in their adjustment speeds, the only exception being firms with low SA scores, which see an increase in their SOA. The former finding is consistent with the evidence of the negative impact of the crisis on the SOA, reported in Tables 6 and 7. With a few exceptions, the decrease in the SOA seems to be mainly driven by reduced external financing activities during the crisis. Next, the finding that firms with low SA scores experience an increase in the SOA during the crisis is inconsistent with the previous results for firm size, one component of the SA index (see column (5) of Table 7). Note that, although the SOA of firms with low SA scores (i.e., more constrained firms) is now larger in magnitude than the SOA of

firms with high SA scores (i.e., less constrained firms) (0.321 versus 0.154), there is no evidence of a threshold effect. Thus, we continue to document little support for the financial constraint view.

Turning to columns (3)–(6), we observe significant threshold effects for the (absolute) deviation variables (in both levels and ratios). Firms with small deviations from their target leverage barely adjust their capital structures: the SOA estimates in columns (3) and (5) are both insignificant. In contrast, firms with large deviations have significantly higher adjustment speeds (12% and 13%). During the crisis period, when it is more costly to make leverage adjustments, firms seem little concerned about small deviations from target leverage. They only have incentives to adjust their capital structures when the deviations become sufficiently large. These findings are in contrast to the full-sample results for the deviation ratio reported in Table 5. However, they are consistent with dynamic leverage rebalancing in the presence of fixed adjustment costs. In addition, they are also in line with the results in Subpanel B2 that firms with higher SOA estimates have significantly larger (absolute) deviations, in both levels and ratios. As in the previous tables, here we document a similar pattern that firms with more rapid adjustments have larger cash flows and financing deficits, which they offset via actively raising capital externally. Further, we also find that these firms are over-levered, thus having stronger incentives to revert to their target leverage.

Robustness Checks: Rolling-regression Analysis

To further examine the robustness of the results, we perform rolling regressions for seven five-year subsamples, starting from 2002–2006 to 2008–2012. The results, summarized in Figure 3, reveal three important patterns. First, consistent with the results in Tables 7 and 8, the Global Financial Crisis has strong and robust, negative effects on the asymmetric adjustment speeds. Our findings here also conform to the results for the linear case reported in Table 6 and Figure 2. Second, in Figures 3.a–3.d, we find moderate evidence that the effects of the crisis on the SOA are asymmetric, as documented in Tables 7 and 8. In particular, the effects seem more pronounced for firms with high growth, large investment, of small size, volatile earnings, and low SA scores, i.e., those with high degrees of financial constraints and higher adjustment speeds pre-crisis. Third, the cross-sectional heterogeneity in the SOA, conditional on the transition variables, is most pronounced before the crisis but becomes weaker both economically and significantly in and around the crisis years. The only two exceptions are the results regarding the absolute deviation, where the cross-sectional variation in the SOA is strongest

during the crisis period (Figures 3.f and 3.g). Overall, our results provide strong evidence of time-varying heterogeneity in the SOA, the heterogeneity caused by the effects of Global Financial Crisis. There is, however, moderate evidence of cross-sectional variation in the SOA.

Figure 3 about here

5 Conclusions

Dynamic trade-off models of capital structure predict that firms facing differential adjustment costs may take different paths toward their target leverage, thereby rendering the SOA heterogeneous. In this paper, we employ dynamic threshold partial adjustment models of leverage to estimate the heterogeneous adjustment speeds for firms with differential adjustment costs, under different regimes and different stages of the business cycle. Specifically, we examine whether the SOA varies with several firm-specific variables that may affect the adjustment costs, namely growth opportunities, investment, firm size, earnings volatility, the Size–Age index, and deviations from target leverage. Further, we study whether the SOA is time-varying and is negatively affected by the Global Financial Crisis.

Using a recent sample period between 2002 and 2012, we obtain the following major findings. First, we document strong and robust evidence of time-varying heterogeneity in the SOA but relatively weaker evidence of cross-sectional variation, especially for the whole sample period. Consistent with our prediction, firms adjust much more slowly during the Global Financial Crisis. However, for the full sample period, there is limited evidence of threshold effects and asymmetric capital structure adjustments conditional on the firm-specific variables proxying for financial constraints. Second, in our subperiod analysis, we document moderate cross-sectional heterogeneity in the SOA, which is generally more pronounced in the pre-crisis years than in crisis years. For the pre-crisis period, more constrained firms, such as those with high growth, with large investment, of small size, with volatile earnings, and with a higher Size–Age index adjust their capital structures faster than their less constrained counterparts. For the crisis period, there is limited evidence on cross-sectional asymmetry in the SOA, conditional on the deviation from target leverage. While firms with a large deviation attempt to move toward their target leverage, albeit with slow speeds, those with a small deviation make no such attempt. Finally, comparing the pre-crisis with crisis results, we find that the effects of the crisis on the adjustment speeds are asymmetric: they are more pronounced for firms with high degrees

of financial constraints and higher adjustment speeds pre-crisis. Overall, our study reveals complex patterns of time-varying and cross-sectional asymmetries in capital structure adjustments, which are in line with dynamic trade-off models.

Our study provides two implications for capital structure studies. First, we show that it is important to allow for both cross-sectional and time-varying heterogeneity in the SOA. In our study, the time-series variation in the SOA is more dominant than the cross-sectional variation. This suggests that research on asymmetric capital structure adjustments that assumes time-invariant adjustment speeds may produce inaccurate estimates of the SOA. Second, inconsistent with our predictions, we find that constrained firms have a higher SOA than unconstrained firms. However, the former firms tend to have large financing deficits, which they offset through external financing activities. These results are in line with the idea that firms can adjust faster, at potentially lower adjustment costs that can be shared with the transaction costs of raising external funds. This argument suggests that the leverage adjustment costs may not be fully proxied by firm-specific measures of financial constraints and that they should be benchmarked against the capital market transaction costs (Faulkender et al., 2012). On the other hand, we demonstrate significantly negative effects of supply-side constraints on capital structure adjustments when exploiting the exogenous credit shock triggered by the Global Financial Crisis. This suggests that supply-side, external measures of financial constraints may play a more important role than firm-specific measures in determining the SOA.

Finally, we conclude with some limitations and avenues for future research. While our study is focused on testing the trade-off theory, it is silent on alternative views of capital structure such as the pecking order theory, the market timing, and inertia hypotheses. Our empirical work is based on an extension of the partial adjustment model of leverage; however, this model has difficulty distinguishing between active target adjustment behavior and mechanical mean reversion (Chen and Zhao, 2007; Chang and Dasgupta, 2009). Hence, it would be interesting for future research to extend our empirical model into a more general approach and estimation method that is able to test alternative theories of capital structure and to account for potential mechanical mean reversion of leverage.

References

- Aivazian, V.A., Ge, Y., Qiu, J., 2005a. The Impact of Leverage on Firm Investment: Canadian Evidence. *Journal of Corporate Finance*, 11, 277–291.
- Almeida, H., Campello, M., 2007. Financial Constraints, Asset Tangibility, and Corporate Investment. *Review of Financial Studies* 20, 1429–1460.
- Altman, E.I., 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance* 23, 589–609.
- Alvarez, J., Arellano, M., 2003. The Time Series and Cross-Section Asymptotics of Dynamic Panel Data Estimators. *Econometrica* 71, 1121–1159.
- Anderson, T.W., Hsiao, C., 1982. Formulation and Estimation of Dynamic Models Using Panel Data. *Journal of Econometrics* 18, 47–82.
- Andrews, D.W.K., Ploberger, W., 1994. Optimal Tests When A Nuisance Parameter Is Present Only under The Alternative. *Econometrica* 62, 1383–1414.
- Andrews, D.W.K., Ploberger, W., 1996. Testing for Serial Correlation Against an ARMA(1, 1) Process. *Journal of the American Statistical Association* 91, 1331–1342.
- Antoniou, A., Guney, Y., Paudyal, K., 2008. The Determinants of Capital Structure: Capital Market Oriented versus Bank Oriented Institutions. *Journal of Financial and Quantitative Analysis* 43, 59–92.
- Arellano, M., 2003. *Panel Data Econometrics: Advanced Texts in Econometrics*. Oxford University Press, Oxford.
- Arellano, M., Bond, S.R., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* 58, 227–297.
- Baker, M., Wurgler, J., 2002. Market Timing and Capital Structure. *Journal of Finance* 57, 1–32.
- Bernanke, B., Gertler, M., 1989. Agency Costs, Net Worth and Business Fluctuations. *American Economic Review* 79, 14–31.
- Bernanke, B., Gertler, M., 1995. Inside the Black Box: the Credit Channel of Monetary Transmission. *Journal of Economic Perspectives* 9, 27–48.
- Blundell, R.W., Bond, S.R., 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics* 87, 115–143.
- Byoun, S., 2008. How and When Do Firms Adjust Their Capital Structures towards Targets? *Journal of Finance* 63, 3069–3096.

- Campello, M., Giambona, E., Graham, J., Harvey, C., 2011. Liquidity Management and Corporate Investment During a Financial Crisis. *Review of Financial Studies* 24, 1944–1979.
- Campello, M., Graham, J., Harvey, C., 2010. The Real Effects of Financial Constraints: Evidence from a Financial Crisis. *Journal of Financial Economics* 97, 470–487.
- Caner, M. and Hansen, B.E., 2004. Instrumental Variable Estimation of a Threshold Model. *Econometric Theory* 20, 813–843.
- Chan, K.S., 1993. Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model. *Annals of Statistics* 21, 520–533.
- Chang, X., Dasgupta, S., 2009. Target Behavior and Financing: How Conclusive is the Evidence. *Journal of Finance* 64, 1767–1796.
- Chen, L., Zhao, Z., 2007. Mechanical Mean Reversion of Leverage Ratios. *Economic Letters* 95, 223–229.
- Campbell, J.L., Dhaliwal, D.S., Schwartz Jr., W.C., 2012. Financing Constraints and the Cost of Capital: Evidence from the Funding of Corporate Pension Funds. *Review of Financial Studies* 25, 868–912.
- Covas, F., Den Haan, W.J., 2011. The Cyclical Behavior of Debt and Equity Finance. *American Economic Review* 101, pp. 877–899.
- Cook, D.O., Tang, T., 2010. Macroeconomic Conditions and Capital Structure Adjustment Speed. *Journal of Corporate Finance* 16, 73–87.
- Dang, V.A., Garrett, I., Nguyen, C., 2011. Asymmetric Partial Adjustment toward Target Leverage: International Evidence. FMA Annual Meetings, Working Paper.
- Dang, V.A., Kim, M., Shin, Y., 2012. Asymmetric Capital Structure Adjustments: New Evidence from Dynamic Panel Threshold Models. *Journal of Empirical Finance* 19, 465–482.
- Elsas, R. and Florysiak, D., 2011. Heterogeneity in the Speed of Adjustment toward Target Leverage. *International Review of Finance* 11, 181–211.
- European Central Bank, 2012. Corporate Indebtedness in the Euro Area. *Monthly Bulletin* February 2012, 87–103.
- Davies, R.B., 1987. Hypothesis Testing When A Nuisance Parameter Is Present Only under The Alternative. *Biometrika* 74, 33–43.
- DeAngelo, H., Masulis, R., 1980. Optimal Capital Structure under Corporate and Personal Taxation. *Journal of Financial Economics* 8, 3–29.
- Drobtz, W., Wanzenried, G., 2006. What Determines the Speed of Adjustment to The Target Capital Structure? *Applied Financial Economics* 16, 941–958.

- Drobetz, W., Pensa, P., Wanzenried, G., 2006. Firm Characteristics and Dynamic Capital Structure Adjustment. Working Paper, University of Hamburg.
- Duchin, R., Ozbas, O., Sensoy, B., 2010. Costly External Finance, Corporate Investment, and the Subprime Mortgage Credit Crisis. *Journal of Financial Economics* 97, 418–435.
- Erel, I., Julio, B., Kim, W., Weisbach, M.S., 2012. Macroeconomic Conditions and Capital Raising. *Review of Financial Studies*, 25, 341–376.
- Fama, E.F., French, K.R., 2002. Testing Trade-Off and Pecking Order Predictions about Dividends and Debt. *Review of Financial Studies* 15, 1–33.
- Faulkender, M.W., Flannery, M.J., Hankins, K.W., Smith, J.M., 2012. Cash Flows and Leverage Adjustments. *Journal of Financial Economics* 103, 632–646.
- Fazzari, S.M., Hubbard, R.G., Petersen, B.C., 1988. Financial Constraints and Corporate Investment. *Brookings Papers on Economic Activity* 2, 141–195.
- Fischer, E.O., Heinkel, R., Zechner, J., 1989. Dynamic Capital Structure Choice: Theory and Tests. *Journal of Finance* 44, 19–40.
- Flannery, M.J., Hankins, K.W., 2013. Estimating Dynamic Panel Models in Corporate Finance. *Journal of Corporate Finance*, Forthcoming.
- Flannery, M.J., Rangan, K.P., 2006. Partial Adjustment toward Target Capital Structures. *Journal of Financial Economics* 79, 469–506.
- Frank, M.Z., Goyal, V.K., 2007. Trade-off and Pecking Order Theories of Debt, in Eckbo, B.E. (ed). *Handbook of Corporate Finance: Empirical Corporate Finance*. North Holland Handbooks of Finance, Elsevier Science, Amsterdam.
- Frank, M., Goyal, V.K., 2009. Capital Structure Decisions: Which Factors Are Reliably Important? *Financial Management* 38, 1–37.
- Gertler, M., Gilchrist, S., 1993. The Role of Credit Market Imperfections in the Monetary Transmission Mechanism: Arguments and Evidence. *Scandinavian Journal of Economics* 95, 43–63.
- Hackbarth, D., Miao, J., Morellec, E., 2006. Capital Structure, Credit risk, and Macroeconomic Conditions. *Journal of Financial Economics* 82, 519–550.
- Hadlock, C.J., Pierce, J.R., 2010. New Evidence on Measuring Financial Constraints: Moving beyond the KZ index. *Review of Financial Studies*, 23, 1909–1940.
- Hall, A., 2005. *Generalized Methods of Moments*. Oxford University Press, Oxford.
- Hanousek, J., Shamshur, A., 2011. A Stubborn Persistence: Is the Stability of Leverage Ratios Determined by the Stability of the Economy? *Journal of Corporate Finance* 17, 1360–1376.

- Hansen, B.E., 1996. Inference When A Nuisance Parameter Is Not Identified under The Null Hypothesis. *Econometrica* 64, 413–430.
- Hansen, B.E., 1999. Threshold Effects in Non-dynamic Panels: Estimation. Testing and Inference. *Journal of Econometrics* 93, 345–368.
- Hansen, B.E., 2000. Sample Splitting and Threshold Estimation. *Econometrica* 68, 575–603.
- Hovakimian, A., Li, G., 2011. In Search of Conclusive Evidence: How to Test for Adjustment to Target Capital Structure. *Journal of Corporate Finance* 17, 33–44.
- Huang, R., Ritter, J.R., 2009. Testing Theories of Capital Structure and Estimating the Speed of Adjustment. *Journal of Financial and Quantitative Analysis* 44, 237–271.
- Ivashina, V., Scharfstein, D., 2010. Bank Lending during the Financial Crisis of 2008. *Journal of Financial Economics* 97, 319–38.
- Jensen, M., 1986. Agency Costs of Free Cash Flow, Corporate Finance and Takeovers. *American Economic Review* 76, 323–339.
- Kaplan, S. N., Zingales, L., 1997. Do Investment–Cash Flow Sensitivities Provide Useful Measures of Financial Constraints? *Quarterly Journal of Economics* 112, 159–216.
- Kiyotaki, N., Moore, J., 1997. Credit Cycles. *Journal of Political Economy* 105, 211–248.
- Korajczyk, R.A., Levy, A. 2003. Capital Structure Choice: Macroeconomic Conditions and Financial Constraints. *Journal of Financial Economics* 68, 75–109.
- Kraus, A., Litzenberger, R.H., 1973. A State-Preference Model of Optimal Financial Leverage. *Journal of Finance* 28, 911–922.
- Lamont, O., Polk, C., Saa-Requejo, J., 2001. Financial Constraints and Stock Returns. *Review of Financial Studies* 14, 529–554.
- Leary, M.T., Roberts, M.R., 2005. Do Firms Rebalance Their Capital Structures. *Journal of Finance* 60, 2575–2619.
- Lee, I., Lochhead, S., Ritter, J., Zhao, Q., 1995. The Costs of Raising Capital. *Journal of Financial Research* 19, 59–74.
- Leland, H.E., 1994. Corporate Debt Value, Bond Covenants, and Optimal Capital Structure. *Journal of Finance* 49, 1213–1252.
- Lemmon, M.L., Roberts, M.R., Zender, J.F., 2008. Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure. *Journal of Finance* 63, 1575–1608.
- MacKie-Mason, J.K., 1990. Do Taxes Affect Corporate Financing Decisions? *Journal of Finance* 45, 1471–1493.

- Maddala, G.S., Nelson, F., 1994. Switching Regression Models with Exogenous and Endogenous Switching, in: Maddala, G. S. (Ed.), *Econometric Methods and Applications*, vol. 2. Edward Elgar, Aldershot, pp. 369–372.
- Modigliani, F., Miller, M.H., 1958, The Cost of Capital, Corporate Finance and the Theory of Investment. *American Economic Review* 49, 261–297.
- Myers, S.C., 1977. Determinants of Corporate Borrowing. *Journal of Financial Economics* 5, 145–175.
- Myers, S.C., 1984. The Capital Structure Puzzle. *Journal of Finance* 34, 575–592.
- Myers, S.C. and Majluf, N.S., 1984. Corporate Financing and Investments Decisions When Firms Have Information That Investors Do Not Have. *Journal of Financial Economics* 13, 187–221.
- Newey W., 1984, A Method of Moments Interpretation of Sequential Estimators. *Economic Letters* 14, 201–206.
- Nickell, S.J., 1981. Biases in Dynamic Models with Fixed Effects. *Econometrica* 49, 1417–1426.
- Ozkan, A., 2001. Determinants of Capital Structure and Adjustment to Long Run Target: Evidence from UK Company Panel Data. *Journal of Business Finance and Accounting* 28, 175–198.
- Pagan, A., 1984. Econometric Issues in the Analysis of Regressions with Generated Regressors. *International Economic Review* 25, 221–247.
- Rajan, R.G., Zingales, L., 1995. What Do We Know about Capital Structure? Some Evidence from International Data. *Journal of Finance* 50, 1421–1461.
- Roodman, D., 2009. How to Do xtabond2: An Introduction to Difference and System GMM in Stata? *Stata Journal*, 9, 86–136.
- Strebulaev, I.A., Yang, B., 2013. The Mystery of Zero-Leverage Firms. *Journal of Financial Economics* 109, 1–23.
- Strebulaev, I.A., 2007. Do Tests of Capital Structure Theory Mean What They Say. *Journal of Finance* 62, 1747–1787.
- Titman, S., Wessels, R., 1988. The Determinants of Capital Structure Choice. *Journal of Finance* 43, 1–19.
- Welch, I., 2004. Capital Structure and Stock Returns. *Journal of Political Economy* 112, 106–131.
- Whited, T., Wu, G., 2006. Financial Constraints Risk. *Review of Financial Studies* 19, 531–559.
- Windmeijer, F., 2005. A Finite Sample Correction for the Variance of Linear Efficient Two-step GMM Estimators. *Journal of Econometrics* 126, 25–51.

Figure 1: Evolution of Leverage

The following figures present the time-series of leverage over the sample period 2002–2012. Figure 1.a presents the mean and median leverage ratios. Figures 1.b reports the leverage ratios of small and large firms, respectively. Figure 1.c reports the leverage ratios of firms with a low Size-Age (SA) index and a high (SA) index, respectively.

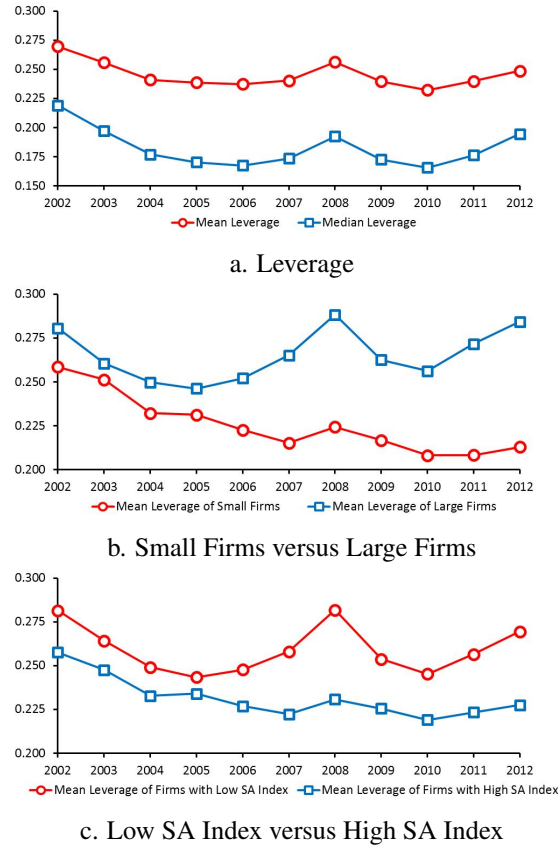


Figure 2: Time-series Variation in the Speed of Adjustment

The following figure presents the time-series variation in the speed of adjustment (SOA) in the linear partial adjustment model (1). The SOA estimates are obtained using the two-step GMM estimator from seven rolling regressions, each for a five-year subsample; the first subsample is 2002–2006 and the last subsample is 2008–2012.

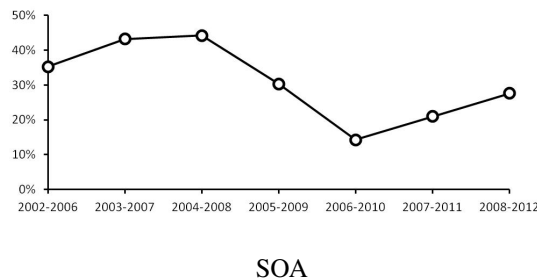


Figure 3: Time-series Variation in the Asymmetric Speed of Adjustment

The following figures report the time-series variation in the asymmetric speed of adjustment (SOA), estimated for the low and high regimes (L, H) of the threshold partial adjustment model (6). The SOA estimates are obtained using the two-step GMM estimator from seven rolling regressions, each for a five-year subsample; the first subsample is 2002–2006 and the last subsample is 2008–2012.

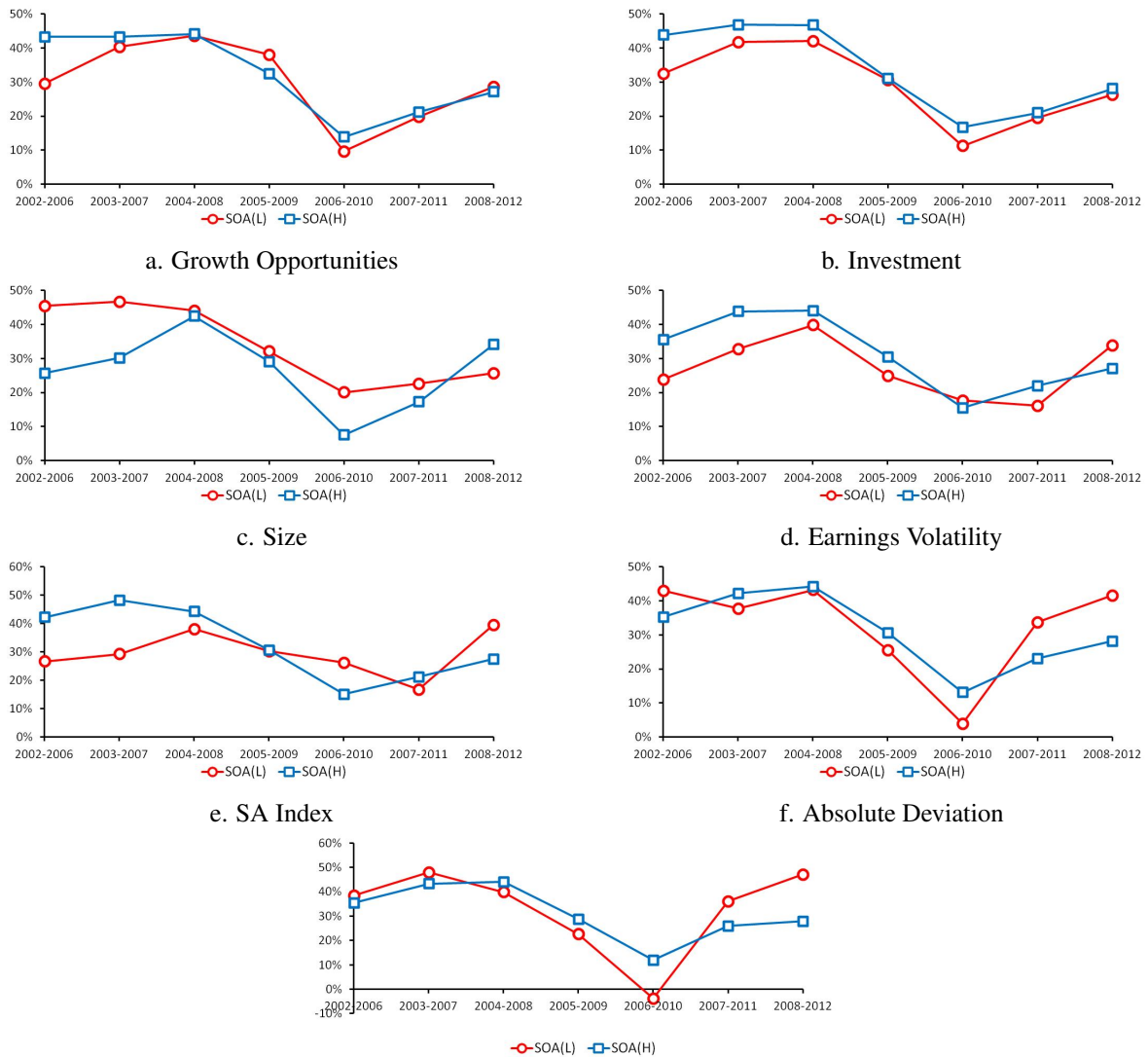


Table 1: Summary Statistics

Variable	Obs	Mean	Median	Stdev	Min	Max	Skew	Kurt
Leverage	51,894	0.245	0.181	0.263	0.000	1.000	1.345	4.342
Profitability	51,894	-0.093	0.043	0.364	-1.213	0.227	-2.052	6.363
Growth Opportunities	51,894	3.111	1.260	7.701	0.243	59.253	5.919	40.277
Depreciation	51,894	0.048	0.036	0.048	0.000	0.327	2.869	14.537
Tangibility	51,894	0.288	0.197	0.264	0.000	0.944	0.923	2.728
Size	51,894	5.053	5.211	2.780	-2.329	10.597	-0.312	2.852
R&D Dummy	51,894	0.546	1.000	0.498	0.000	1.000	-0.185	1.034
R&D Expenditure	51,894	0.066	0.000	0.167	0.000	1.014	3.984	20.258
Industry Median Leverage	51,894	0.173	0.182	0.104	0.000	0.489	0.195	2.335
Investment	49,948	0.156	0.000	0.495	0.000	4.069	5.836	41.557
Earnings Volatility	33,988	0.395	0.062	1.644	0.009	13.565	6.883	52.340
SA Index	51,894	-2.739	-3.076	1.114	-3.918	1.698	1.783	6.582
Cash Flow	51,248	-0.288	0.020	1.267	-8.954	0.445	-5.537	35.494
Financing Deficit	46,934	0.106	0.005	0.410	-0.820	2.456	3.520	19.599
Net Debt Issued	51,238	0.011	0.000	0.211	-1.000	0.960	0.079	14.717
Net Equity Issued	47,561	0.086	0.001	0.286	-0.162	1.787	4.071	21.246

Notes: This table provides summary statistics for the variables considered in the paper. Obs, Stdev, Skew, and Kurt are the number of observations, standard deviation, skewness, and kurtosis, respectively. The data set is a panel of US firms collected from the Compustat database for the period 2002–2012. Following Flannery and Rangan (2006) and most recent capital structure studies (Faulkender et al., 2012; Strebulaev and Yang, 2013), we define the variables used in the target leverage model (2), as follows. Leverage is the ratio of total debt, including debt of both long-term and short-term maturities, to total assets $((dlt + dlrt)/at)$. Profitability is the ratio of earnings before interest and taxes to total assets $((ib + xint + txt)/at)$. Growth opportunities (market-to-book) is the ratio of total liabilities plus the market value of equity to total assets $((dlc + dlrt + pstkl + csho * prcc_f)/at)$. Depreciation is the ratio of depreciation to total assets (dp/at) . Tangibility is the ratio of property, plant, and equipment to total assets $(ppent/at)$. The industry median leverage ratio is calculated based on Fama and French’s 49 industry groupings. R&D expenses is the ratio of R&D expenses to total assets (xrd/at) . The R&D dummy variable is equal to 1 if the firm did not report R&D expenses and 0 otherwise. Size is the natural log of total assets, measured in 2000 dollars $(\ln(at * CPI_{2000}/CPI))$, where CPI is the consumer price index). The rest of the variables are measured as follows. Investment is capital expenditure less depreciation divided by lagged fixed assets $((capx - dp)/l.ppent)$ (Aivazian et al., 2005). Earnings volatility is the volatility of profitability calculated for the past 10 years (minimum 3 years of data required) (Strebulaev and Yang, 2013). The SA index is the Size and Age index calculated as $(-0.73 * \ln TA + 0.043 * \ln TA^2 - 0.040 * Age)$, where Age is the age of the company since the IPO date and is capped at 37 (Hadlock and Pierce, 2010). Cash flow is the ratio of operating income before depreciation less total taxes and interest to the lagged value of total assets, less ind_capex , which is the industry median of net investment $((oibdp - xint - txt)/l.at - ind_capex)$ (Faulkender et al., 2012). Financing deficit is the sum of net debt and equity issued, where net debt issued is the ratio of the change in current and long-term debt to total assets $((dlc + dlrt) - (l.dlc + l.dlrt))/at$ and net equity issued is the ratio of net equity issuance to total assets $((sstk - prstk)/at)$ (Strebulaev and Yang, 2013).

Table 2: Regression Results for Target Leverage and (One-stage) Partial Adjustment Models

Independent Variable	Target Leverage Model		Partial Adjustment Model	
	POLS (1)	FE (2)	AH-IV (3)	GMM (4)
Lagged Leverage	-	-	0.687*** (0.028)	0.713*** (0.024)
Profitability	-0.177*** (0.007)	-0.093*** (0.008)	0.031*** (0.010)	0.041*** (0.010)
Growth Opportunities	0.006*** (0.000)	0.001* (0.000)	-0.003*** (0.001)	-0.003*** (0.001)
Depreciation	0.495*** (0.036)	0.147*** (0.057)	-0.269*** (0.076)	-0.239*** (0.074)
Size	0.009*** (0.001)	0.005* (0.003)	0.014*** (0.005)	0.012*** (0.005)
Tangibility	0.046*** (0.005)	0.106*** (0.016)	-0.025 (0.022)	-0.030 (0.021)
R&D Dummy	0.024*** (0.003)	0.007 (0.009)	-0.005 (0.011)	-0.003 (0.011)
R&D Expenses	-0.017 (0.015)	0.022 (0.022)	-0.032 (0.024)	-0.021 (0.024)
Industry Median of Leverage	0.616*** (0.012)	0.095** (0.038)	-0.289*** (0.048)	-0.264*** (0.046)
Time Dummies	No	No	Yes	Yes
Implied SOA	-	-	0.313	0.287
Observations	45,662	45,662	39,430	39,430
Adj. R-squared	0.17	0.11	-	-
Hausman Test	-	1130.26 [0.00]	-	-
AR(2) Test	-	-	-0.39 [0.70]	-0.34 [0.74]
Sargan Test	-	-	-	84.5 [0.00]

Notes: SOA is the speed of adjustment. POLS and FE are the pooled OLS and fixed-effects estimators, respectively. AH-IV stands for the Anderson-Hsiao just-identified instrumental variable estimator and GMM refers to the two-step GMM estimator. Hausman test is a test for potential significant differences in the fixed-effects (FE) and random effects (RE) estimations, and is asymptotically distributed as χ^2 under the null of no difference. AR(2) test is a test for the second-order serial correlation, and is asymptotically distributed as $N(0, 1)$ under the null of no serial correlation. Sargan test is a test for the null of valid instruments and is asymptotically distributed as χ^2 under the null. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels, respectively. Figures in (\cdot) are the standard errors of the coefficients and those in $[\cdot]$ are the p -values of the test statistics. See notes to Table 1 for variable definitions.

Table 3: Partial Adjustment Model of Leverage – Two-Stage Estimation

	POLS (1)	FE (2)	AH-IV (3)	GMM (4)
SOA	0.183*** (0.005)	0.528*** (0.010)	0.334*** (0.024)	0.308*** (0.020)
Time Dummies	Yes	Yes	Yes	Yes
First Differences	No	No	Yes	Yes
Observations	45,662	45,662	39,430	39,430
Adj. R-squared	0.09	0.09	-	
AR(2) Test	-	-	0.23 [0.82]	0.26 [0.80]
Sargan Test	-	-	-	88.64 [0.00]

Notes: SOA is the speed of adjustment. POLS and FE are the pooled OLS and fixed-effects estimators, respectively. AH-IV stands for the Anderson-Hsiao just-identified instrumental variable estimator and GMM refers to the two-step GMM estimator. See Table 2 for notes about the AR(2) and Sargan diagnostic tests. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels, respectively. Figures in (·) are the standard errors of the coefficients and those in [·] are the p-values of the test statistics. See also notes to Table 1 for variable definitions.

Table 4: Dynamic Panel Threshold Model of Leverage Conditional on Single Firm Characteristics

Transition Variable Regime	Growth Opportunities		Investment		Size		Earnings Volatility	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A. Estimation and Test Results</i>								
SOA	0.303*** (0.022)	0.328*** (0.020)	0.301*** (0.020)	0.355*** (0.024)	0.348*** (0.027)	0.302*** (0.027)	0.265*** (0.040)	0.337*** (0.024)
Observations	10,503	41,391	35,558	16,336	22,831	29,063	4,964	46,930
Threshold (Coverage)	0.81375 (23%)		0.16066 (81%)		5.22180 (50%)		0.02511 (17%)	
Confidence Interval	[0.81363,0.81386]		[0.16031,0.16084]		[5.21969,5.22228]		[0.02510,0.02513]	
AR(2) Test	0.23 [0.81]		0.24 [0.81]		0.22 [0.83]		0.22 [0.82]	
Sargan Test	78.36 [0.00]		71.70 [0.01]		39.33 [0.00]		38.26 [0.00]	
Threshold Test	1.92 [0.16]		7.64 [0.01]		1.83 [0.17]		3.84 [0.04]	
<i>Panel B. Firm Characteristics</i>								
Leverage	0.216	0.253 ^a	0.252	0.230 ^a	0.224	0.262 ^a	0.276	0.242 ^a
Deviation	-0.031	0.004 ^a	0.005	-0.036 ^a	-0.021	0.012 ^a	0.013	-0.006 ^a
Absolute Deviation	0.136	0.189 ^a	0.173	0.191 ^a	0.211	0.144 ^a	0.129	0.183 ^a
Absolute Deviation Ratio	0.622	0.974	0.895	0.893	1.167	0.636 ^a	0.522	0.943
Cash Flow	-0.034	-0.354 ^a	-0.208	-0.469 ^a	-0.620	-0.021 ^a	0.054	-0.325 ^a
Financing Deficit	0.007	0.132 ^a	0.070	0.187 ^a	0.204	0.027 ^a	-0.005	0.118 ^a
Net Debt Issued	-0.012	0.017 ^a	0.005	0.026 ^a	0.018	0.006 ^a	0.006	0.012 ^b
Net Equity Issued	0.018	0.104 ^a	0.057	0.151 ^a	0.159	0.029 ^a	-0.010	0.096 ^c

Notes: SOA is the speed of adjustment. All models are estimated in first differences by the two-step GMM and include time dummies. The confidence interval for the threshold parameter estimate is obtained using Hansen's (1999) approach. See Table 2 for notes about the AR(2) and Sargan diagnostic tests. Threshold test is a test under the null of no threshold effect; its p-value is evaluated by a bootstrap-based procedure. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels. a, b, and c indicate that firm characteristics in the low and high regimes are statistically different from each other at the 1%, 5%, and 10% levels. Figures in (·) are the standard errors of the coefficients and those in [·] are the p-values of the statistics. See also notes to Table 1 for variable definitions.

Table 5: Dynamic Panel Threshold Model of Leverage Conditional on Composite Measures of Financial Constraints and Target Leverage Deviations

Transition Variable Regime	SA Index		Absolute Deviation		Absolute Deviation Ratio	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A. Estimation and Test Results</i>						
SOA	0.340*** (0.050)	0.325*** (0.019)	0.281*** (0.050)	0.321*** (0.020)	0.362*** (0.025)	0.312*** (0.020)
Observations	6,850	45,044	8,675	43,219	25,236	26,658
Threshold (Coverage)	-3.65169 (15%)		0.06420 (22%)		0.97441 (64%)	
Confidence Interval	[-3.65169,-3.64875]		[0.06418,0.06425]		[0.97427,0.97449]	
AR(2) Test	0.24 [0.81]		0.22 [0.83]		0.30 [0.77]	
Sargan Test	70.59 [0.01]		72.97 [0.00]		69.88 [0.01]	
Threshold Test	0.10 [0.76]		0.70 [0.43]		6.10 [0.02]	
<i>Panel B. Firm Characteristics</i>						
Leverage	0.266	0.242 ^a	0.231	0.248 ^a	0.246	0.245
Deviation	0.009	-0.007 ^a	-0.004	-0.004	-0.025	0.033 ^a
Absolute Deviation	0.122	0.188 ^a	0.032	0.218 ^a	0.115	0.286 ^a
Absolute Deviation Ratio	0.518	0.974 ^c	0.177	1.098 ^a	0.446	1.693 ^a
Cash Flow	0.056	-0.341 ^a	-0.030	-0.341 ^a	-0.184	-0.389 ^a
Financing Deficit	-0.011	0.124 ^a	0.031	0.121 ^a	0.073	0.138 ^a
Net Debt Issued	0.007	0.012 ^c	0.007	0.012 ^b	0.016	0.007 ^a
Net Equity Issued	-0.016	0.102 ^a	0.023	0.099 ^a	0.048	0.123 ^a

Notes: SOA is the speed of adjustment. All models are estimated in first differences by the two-step GMM and include time dummies. The confidence interval for the threshold parameter estimate is obtained using Hansen's (1999) approach. See Table 2 for notes about the AR(2) and Sargan diagnostic tests. Threshold test is a test under the null of no threshold effect; its p-value is evaluated by a bootstrap-based procedure. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels. a, b, and c indicate that firm characteristics in the low and high regimes are statistically different from each other at the 1%, 5%, and 10% levels. Figures in (·) are the standard errors of the coefficients and those in [·] are the p-values of the statistics. See also notes to Table 1 for variable definitions.

Table 6: Linear Partial Adjustment Model of Leverage – The Impact of the Global Financial Crisis

	Dummy-variable Approach	Sample-splitting Approach	
	(1)	Pre-crisis Period (2)	Crisis Period (3)
SOA	0.338*** (0.019)	0.375*** (0.026)	0.144*** (0.049)
SOA _{FC}	-0.047*** (0.011)		
Observations	39,430	18,499	13,347
AR(2) Test	0.25 [0.80]	0.97 [0.43]	-0.68 [0.49]
Sargan Test	38.00 [0.02]	14.43 [0.11]	9.19 [0.10]

Notes: SOA is the speed of adjustment. In column (1), SOA_{FC} captures the impact of the Global Financial Crisis on the SOA: it is the coefficient on the crisis dummy variable that takes the value 1 if the year is between 2007 and 2009, and 0 otherwise. In columns (2) and (3), the pre-crisis period is 2002–2006 and the crisis period is 2006–2010. All models are estimated in first differences by the two-step GMM; the regressions in columns (2) and (3) also include time dummies. The confidence interval for the threshold parameter estimate is obtained using Hansen’s (1999) approach. See Table 2 for notes about the AR(2) and Sargan diagnostic tests. Threshold test is a test under the null of no threshold effect; its p-value is evaluated by a bootstrap-based procedure. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels. Figures in (·) are the standard errors of the coefficients and those in [·] are the p-values of the statistics. See also notes to Table 1 for variable definitions.

Table 7: Dynamic Panel Threshold Model of Leverage Conditional on Single Firm Characteristics – Results for the Pre-crisis and Crisis Periods

Transition Variable Regime	Growth Opportunities		Investment		Size		Earnings Volatility	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A. Pre-crisis Period</i>								
<i>A1. Estimation and Test Results</i>								
SOA	0.296*** (0.033)	0.433*** (0.045)	0.324*** (0.033)	0.439*** (0.043)	0.441*** (0.048)	0.258*** (0.037)	0.240*** (0.050)	0.356*** (0.034)
Observations	15,800	8,295	15,574	8,521	3,046	21,049	8,136	15,959
Threshold (Coverage)	3.40798 (83%)		0.18760 (85%)		2.03460 (16%)		0.11414 (72%)	
Confidence Interval	[3.39866,3.41217]		[0.18456,0.18760]		[2.01967,2.04408]		[0.11409,0.11418]	
AR(2) Test	0.89 [0.37]		0.93 [0.35]		0.96 [0.34]		0.84 [0.40]	
Sargan Test	13.67 [0.19]		14.44 [0.15]		10.86 [0.37]		13.05 [0.22]	
Threshold Test	10.60 [0.00]		9.27 [0.00]		10.63 [0.00]		5.15 [0.03]	
<i>A2. Firm Characteristics</i>								
Leverage	0.234	0.283 ^a	0.250	0.252	0.368	0.233 ^a	0.236	0.258 ^a
Deviation	-0.005	-0.008	0.002	-0.040 ^a	0.045	-0.015 ^a	-0.002	-0.009 ^c
Absolute Deviation	0.157	0.287 ^a	0.175	0.204 ^a	0.319	0.155 ^a	0.140	0.213 ^a
Absolute Deviation Ratio	0.722	1.415 ^a	0.760	1.255 ^a	1.597	0.710 ^a	0.634	1.023 ^a
Cash Flow	-0.032	-0.893 ^a	-0.242	-0.474 ^a	-2.008	-0.076 ^a	0.044	-0.512 ^a
Financing Deficit	0.035	0.269 ^a	0.084	0.167 ^a	0.526	0.051 ^a	-0.001	0.174 ^a
Net Debt Issued	0.002	0.024 ^a	0.006	0.016 ^a	0.067	0.001 ^a	0.001	0.014 ^a
Net Equity Issued	0.033	0.213 ^a	0.068	0.140 ^a	0.376	0.052 ^a	-0.001	0.144 ^a
<i>Panel B. Crisis Period</i>								
<i>B1. Estimation and Test Results</i>								
SOA	0.104* (0.063)	0.140*** (0.049)	0.110** (0.053)	0.167*** (0.051)	0.200*** (0.060)	0.078 (0.058)	0.237*** (0.087)	0.154*** (0.049)
Observations	2,752	20,587	13,871	9,468	4,770	18,569	1,798	21,541
Threshold (Coverage)	0.66017 (15%)		0.17490 (79%)		3.48630 (26%)		0.02407 (15%)	
Confidence Interval	[0.66017,0.66057]		[0.17451,0.17686]		[3.48410,3.48765]		[0.02407,0.02414]	
AR(2) Test	-0.68 [0.50]		-0.69 [0.49]		-0.73 [0.46]		-0.68 [0.50]	
Sargan Test	13.20 [0.21]		10.83 [0.37]		19.06 [0.04]		15.42 [0.12]	
Threshold Test	0.80 [0.39]		2.78 [0.10]		2.94 [0.10]		1.11 [0.30]	
<i>B2. Firm Characteristics</i>								
Leverage	0.174	0.246 ^a	0.252	0.216 ^a	0.261	0.232 ^a	0.286	0.233 ^a
Deviation	-0.056	0.016 ^a	0.011	-0.029 ^a	0.009	0.000 ^c	0.023	0.000 ^a
Absolute Deviation	0.128	0.188 ^a	0.174	0.186 ^a	0.244	0.154 ^a	0.130	0.182 ^a
Absolute Deviation Ratio	0.641	0.867 ^a	0.802	0.914 ^a	1.147	0.717 ^a	0.517	0.861 ^a
Cash Flow	-0.054	-0.301 ^a	-0.185	-0.403 ^a	-1.032	-0.073 ^a	0.054	-0.299 ^a
Financing Deficit	0.007	0.115 ^a	0.055	0.174 ^a	0.315	0.047 ^a	-0.011	0.112 ^a
Net Debt Issued	-0.017	0.016 ^a	-0.001	0.031 ^a	0.027	0.008 ^a	0.003	0.013 ^c
Net Equity Issued	0.024	0.092 ^a	0.049	0.135 ^a	0.239	0.044 ^a	-0.012	0.092 ^a

Notes: SOA is the speed of adjustment. All models are estimated in first differences by the two-step GMM and include time dummies. The confidence interval for the threshold parameter estimate is obtained using Hansen's (1999) approach. See Table 2 for notes about the AR(2) and Sargan diagnostic tests. Threshold test is a test under the null of no threshold effect; its p-value is evaluated by a bootstrap-based procedure. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels. a, b, and c indicate that firm characteristics in the low and high regimes are statistically different from each other at the 1%, 5%, and 10% levels. Figures in (·) are the standard errors of the coefficients and those in [·] are the p-values of the statistics. See also notes to Table 1 for variable definitions.

Table 8: Dynamic Panel Threshold Model of Leverage Conditional on Composite Measures of Financial Constraints and Target Leverage Deviations – Results for the Precrisis and Crisis Periods

Transition Variable Regime	SA Index		Absolute Deviation		Absolute Deviation Ratio	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
<i>Panel A. Pre-crisis Period</i>						
<i>A1. Estimation and Test Results</i>						
SOA	0.268*** (0.038)	0.422*** (0.046)	0.441*** (0.135)	0.352*** (0.033)	0.388*** (0.052)	0.354*** (0.032)
Observations	15,990	8,105	2,236	21,859	8,385	15,710
Threshold (Coverage)	-1.64512 (84%)		0.04588 (16%)		0.88126 (60%)	
Confidence Interval	[-1.65225,-1.64185]		[0.04536,0.04665]		[0.88095,0.88155]	
AR(2) Test	0.92 [0.36]		0.84 [0.40]		0.81 [0.42]	
Sargan Test	11.18 [0.34]		11.11 [0.13]		11.15 [0.13]	
Threshold Test	7.83 [0.00]		0.45 [0.50]		0.69 [0.40]	
<i>A2. Firm Characteristics</i>						
Leverage	0.224	0.303 ^a	0.231	0.252 ^a	0.248	0.252
Deviation	-0.014	0.041 ^a	-0.002	-0.006 ^a	-0.017	0.011 ^a
Absolute Deviation	0.155	0.321 ^a	0.023	0.210 ^a	0.106	0.290 ^a
Absolute Deviation Ratio	0.714	1.593 ^a	0.112	0.987 ^a	0.398	1.520 ^a
Cash Flow	-0.014	-0.951 ^a	-0.061	-0.349 ^a	-0.226	-0.375 ^a
Financing Deficit	0.035	0.269 ^a	0.045	0.120 ^a	0.081	0.130 ^a
Net Debt Issued	0.003	0.021 ^a	0.007	0.010	0.015	0.006 ^a
Net Equity Issued	0.032	0.214 ^a	0.035	0.100 ^a	0.059	0.113 ^a
<i>Panel B. Crisis Period</i>						
<i>B1. Estimation and Test Results</i>						
SOA	0.321*** (0.105)	0.154*** (0.048)	0.043 (0.066)	0.133*** (0.049)	-0.044 (0.099)	0.118** (0.052)
Observations	2,935	20,404	10,945	12,394	6,274	17,065
Threshold (Coverage)	-3.68594 (16%)		0.27178 (82%)		0.69367 (47%)	
Confidence Interval	[-3.68633,-3.68578]		[0.27138,0.27193]		[0.69309,0.69957]	
AR(2) Test	-0.67 [0.50]		-0.81 [0.42]		-0.82 [0.41]	
Sargan Test	14.20 [0.16]		8.04 [0.33]		6.37 [0.50]	
Threshold Test	2.42 [0.13]		5.19 [0.03]		5.10 [0.03]	
<i>B2. Firm Characteristics</i>						
Leverage	0.271	0.233 ^a	0.192	0.278 ^a	0.263	0.228 ^a
Deviation	0.010	0.001 ^c	-0.042	0.204 ^a	-0.009	0.013 ^a
Absolute Deviation	0.123	0.188 ^a	0.119	0.442 ^a	0.086	0.258 ^a
Absolute Deviation Ratio	0.510	0.893 ^a	0.615	1.787 ^a	0.325	1.270 ^a
Cash Flow	0.056	-0.320 ^a	-0.084	-0.442 ^a	-0.139	-0.321 ^a
Financing Deficit	-0.016	0.119 ^a	0.049	0.151 ^a	0.048	0.122 ^a
Net Debt Issued	0.001	0.014 ^a	0.005	0.018 ^a	0.002	0.016 ^a
Net Equity Issued	-0.014	0.098 ^a	0.039	0.123 ^a	0.037	0.101 ^a

Notes: SOA is the speed of adjustment. All models are estimated in first differences by the two-step GMM and include time dummies. The confidence interval for the threshold parameter estimate is obtained using Hansen's (1999) approach. See Table 2 for notes about the AR(2) and Sargan diagnostic tests. Threshold test is a test under the null of no threshold effect; its p-value is evaluated by a bootstrap-based procedure. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels. a, b, and c indicate that firm characteristics in the low and high regimes are statistically different from each other at the 1%, 5%, and 10% levels. Figures in (·) are the standard errors of the coefficients and those in [·] are the p-values of the statistics. See also notes to Table 1 for variable definitions.